Designing a Report Recommendation Assistant: A First Design Cycle

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Abstract. Employees often supplement their organization's Business Intelligence (BI) system with individually tinkered reports. Unfortunately, these supplements bear numerous threats such as limited report reuse across all users of the BI system. Therefore, we established a design science research (DSR) project by exploring impediments of existing BI systems, building meta-requirements and suggesting design principles. In particular, we propose a Report Recommendation Assistant (RRA) for improving reuse of reports across potential users.

In this paper, we present our DSR project and focus on the first evaluation cycle. Our results indicate that the RRA has a positive impact on perceived ease of use and perceived usefulness of the BI system. Furthermore, we find that these effects are negatively moderated by user's expertise in using the BI system and are not biased by the underlying BI system. Finally, we leverage results from BI expert interviews and existing literature to refine the proposed RRA.

Keywords: Business intelligence · Design science research · Diffusion of reports · Report reuse · Recommendation assistant

1 Introduction

Over the last decade, many organizations 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 these systems oftentimes do not achieve the expected 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, these individually supplemented systems come along with dangerous threats 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 systems that empower users and provide them with the flexibility to create new output [5]. This

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applies especially to Business Intelligence (BI) systems because (1) many users of BI systems frequently develop supplementary, individually tinkered reports [6] and (2) reuse of these reports across potential users is typically very low [4]. Consequently, an examination of possibilities for simultaneously increasing report reuse and users' flexibility with regards to report development would be highly interesting for industry and academia.

Our overall research project aims at designing such a BI system. As part of this research project, we address the following research question in this paper: *How to design a BI system that improves reuse of reports across employees without limiting employees' abilities to individualize their own reports?*

To answer this question, we first present our DSR project and then present two quantitative evaluation and one qualitative refinement study. In particular, the remainder of this paper is structured as follows: Section 2 shortly introduces related work. Section 3 briefly summarizes our overall DSR project. Upon our previous work [7], we now present instantiations of the proposed design principle as well as testable hypotheses for confirming or rejecting the proposed impact of the design principle. Furthermore, section 4 outlines our research methodology and section 5 presents our results. Section 6 discusses and refines the proposed design principle. Finally, section 7 concludes our work and outlines the next steps of our DSR project.

2 Related Work

In this paper, we investigate reuse of reports across users. Extant literature indicates tensions between reuse of reports and development of new reports that needed to be balanced by organizations [2], [4]. On the one hand, BI systems need to foster user's "ability to create, generate, or produce a new output, structure or behavior without any input from the originator of the system" [5, p. 750]. That is, they need to be flexible and empower users to quickly make use of this flexibility [8]; e.g. through quickly developing new reports [9], [10]. On the other hand, however, BI systems need to be stable because stability is a precondition for reuse of reports across users as well as a precondition for being able to develop new reports in the long run [5]. As a consequence, BI system designers need to balance the tensions [11] between developing additional reports within the BI system and reusing existing reports across users [12].

In particular, our work aims at increasing diffusion of reports. That is, reuse of reports across different employees or, more precisely, the number of employees who are using a certain report [13].

Diffusion of reports is important for organizations because more employees can benefit from the same report; thus generating scale effects (e.g., with regards to report development, maintenance and execution) and ultimately increasing the report's value for its organization. Diffusion 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 deemed available knowledge about a technology to be a major driver of diffusion of that technology. 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 found an impact 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 influences 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.

Synthesizing related work, we infer that diffusion refers to the increasing number of users who adopt a certain technology over time. Upon this understanding, we adopt the notion of report diffusion to refer to the number of employees who use a certain report at a certain minimum frequency. Although little report diffusion is a problem many organizations are facing, existing research does not yet prescribe how to tackle it while preserving employees' abilities to individualize their own reports.

3 Design Science Research Project – An Overview

The work presented in this paper is part of a larger research project with the goal of designing a BI system which facilitates balancing report reuse and development of new reports. Specifically, we established a design science research (DSR) project to address our research questions because DSR is particularly suited to theoretically prescribe how to do something [19]. In particular, this paper focuses on improving reuse of reports across users of the BI system without limiting their ability to develop new, individual reports.

Researchers have recommended DSR to investigate complex, non-decomposable research and business problems [20-21], understand and change generative events [22], and highlight knowledge creation based on rigorous validations [23-24]. According to Hevner [25], 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 [26]. Second, researchers should rigorously make use of the extant scientific knowledge base and theorize meta-attributes of the pursued future system [25]. These meta-attributes are usually referred to as meta-requirements (MRs; [27]) because they reflect generic requirements that need to be met. 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 during multiple cycles [20], [25].

As a part of our overall DSR project, in this paper we focus on the instantiation, evaluation and refinement phases of the first design science cycle. Therefore, we only briefly present impediments to existing BI systems and only briefly introduce one of our identified meta-requirements and one of our proposed design principles [7].

3.1 Problem Awareness and Suggestion

As the exploration of impediments requires flexibility for examining aspects of report diffusion that may not be completely identifiable at the outset of the study, we conducted an exploratory interview study [28]. This is a common approach for establishing DSR projects [26]. Four sites were selected on the basis of theoretical relevance and to ensure an adequate foundation for comparison and to maximize variation [29]. Specifically, we selected two organizations that focus on stability and two organizations that focus on flexibility. Furthermore, since literature indicates a beneficial effect on balancing stability and flexibility from establishing additional specialized organizational units between end users and IT professionals [30], 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 systems across a company [30]. Furthermore, in order to mitigate industry biases, all four organizations are vehicle manufacturing companies. In total, we interviewed 20 employees in order to reveal impediments of current BI systems. [7] provides details about the selected organizations, the chosen snowball sampling approach, participants, semi-structured interview questions, data triangulation and the step-wise coding process.

The interview study indicated that diffusion of reports across the users of a BI system represents a major challenge for organizations. Moreover, the interview study revealed impediments to diffusion of reports across the users of a BI system. For instance, a BICC expert at one organization explained how he believes that the reason why end users tailor their own individual reports would not be a lack of reports or a misfit of existing reports to users' needs. Rather, the problem would be that users would not be able to retrieve the reports they were looking for: "*We have very detailed possibilities for analyses. […] I fear it is less a problem that a required report does not exist. Rather the user gets buried by the bulk of options for selecting the report.*"

This impediment adversely affects diffusion, because the ability to find a report is a precondition for an employee to reuse another employee's report. Too many options create huge complexity and intransparency over existing reports. To work around this impediment, end users start creating new reports instead of searching and reusing existing reports. Ultimately, this fuels a vicious circle. If employees create new reports because they cannot find their required reports, they further increase the number of reports and, thus, make retrieval of reports even more difficult. This is bad for their organizations because if existing reports are less often reused across individual teams and departments, achieving scale effects and operational efficiency becomes more difficult [2], [4-5].

Similarly, it is difficult for BI experts and administrators to identify reports that were developed by a specific employee but might also be useful to further employees. For instance, an interviewee at another organization who focuses on maintaining the organization's BI system complaints about the increasing number of reports: *"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."*

To tackle issues of little diffusion, extant literature has shown that diffusion increases through social influence [31], [32]. Potential new users typically turn to prior users as socially influential referents for determining the appropriate adoption choice [31]. However, contagious social influences of different prior users are not constant [33-34]. Therefore, they should be made visible to potential new users. Building on the findings from our exploratory interview study and extant literature, we derive a first meta-requirement which should be addressed in order to improve diffusion of reports across all users of the BI system.

> ***MR1.*** *In order to increase diffusion of a report, a BI system should make the social influence of previous users on a potential new user visible.*

As explained above, a BI system needs to improve visibility of the social influence of prior report users in order to improve diffusion of a specific report. Building on literature, a key factor for improving visibility is user guidance as it allows focusing a user's attention on desired information and functionalities. In the 1990s, Silver [35] started examining possibilities for decisional guidance and their potential impacts. Briefly after that, Dhaliwal and Benbasat [36] 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 [37]. More recently, guidance studies highlighted the need for recommendation assistants. Especially in the field of e-commerce, recommendation assistants who provide additional information and explanations have been found to focus customers' attention and affect their shopping behavior [38]. 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 propose the usage of a report recommendation assistant (RRA) as a response to MR1.

> ***DP1.*** *In order to increase diffusion of reports, the BI system should recommend reports upon the social influence of previous users on the user.*

3.2 Instantiations

Design principles usually can be implemented in multiple different ways. This particularly accounts to BI systems because they are also composed of different architectural layers (e.g., database system, data warehouse, and reporting client). Thus, we first had to decide on which layer the RRA should be implemented. We opted for the client layer because only an extension to the BI client may sense the user's environment and, thus, analyze the user's currently selected data. Server-side layers (e.g., database and data warehouse) can only analyze which queries are executed by the user; but not which subset of all the data returned by a particular query is actually being filtered for analysis.

As a first running prototype, we implemented the aforementioned RRA as an extension to the BI client *SAP BusinessObjects Office Analysis*. Since this BI client itself is an extension to *Microsoft Excel*, the RRA looks and feels like an extension to *Microsoft Excel*. Regarding its capabilities, this RRA is able to access metadata from the central BI system and combine this information with contextual information such as currently filtered dimensions. The RRA recommends frequently used reports developed by prior users who have been investigating similar dimensions and are using similar data filters and, thus, have a high social influence on the current user [31]. Fig. 1 shows a screen-shot of our prototype.

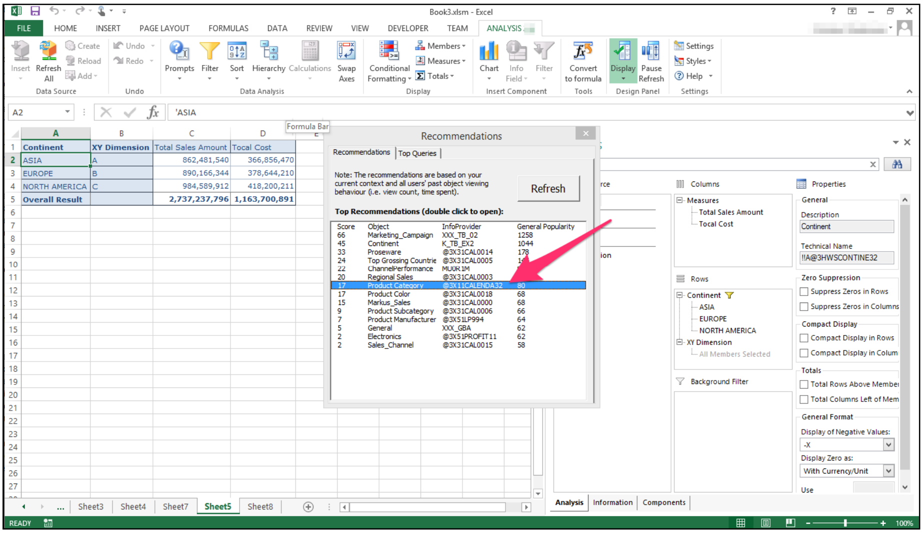

Fig. 1. Instantiation of a working RRA prototype

In addition, we developed alternative user interface mockups of three popular BI clients that were extended by the same RRA. Thus, we were able to control for potential biasing effects resulting from the BI client. Specifically, we instantiated the RRA as a side panel to three common types of BI clients [39]: First, we instantiated the RRA as an extension to a BI client which is typically used for agile business analysis and accessing data from rather small and medium BI systems, i.e., *Tableau Desktop*. Second, we instantiated the RRA as an extension to a BI client which is typically used for accessing data from a large, global BI system, i.e., *SAP BW/BO*. Finally, third, we instantiated the RRA as an extension to a BI client which itself extends *Microsoft Excel*. *Microsoft Excel*-based BI clients are provided by all large BI vendors in order to offer users ways to access large, global BI systems in familiar ways. We extended each of the three BI clients with a side panel that recommends additional reports based on the social influence of previous users and similarity to the currently viewed data. Fig. 2 and Fig. 3 show the RRA (i.e., the panel at the right side of the screen) as an extension to the three BI clients.

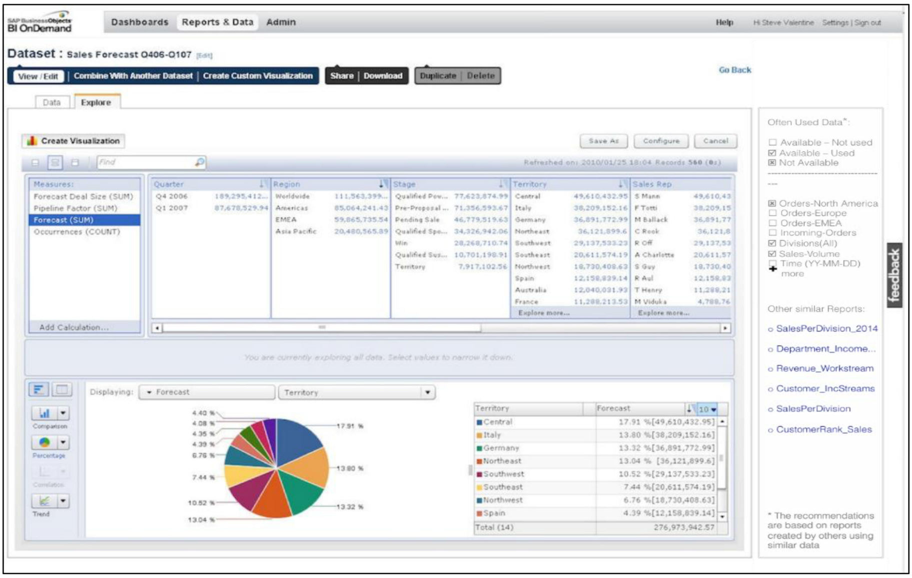

Fig. 2. SAP BW/BO extended with the RRA (panel on the right side)

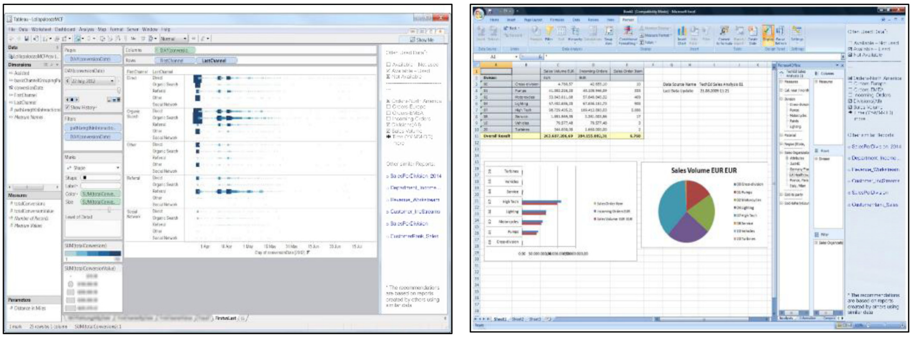

Fig. 3. Tableau Desktop (left) and MS Excel-based BI client (right) extended with the RRA

3.3 Testable Hypotheses

The goal of our work is to design a BI system that increases diffusion of reports. However, as empirically measuring diffusion of reports requires measuring usage of reports at multiple points in time [13], the work presented in this paper focuses on measuring antecedents of usage in a first step. In particular, we focus on perceived ease of use (PEOU) and perceived usefulness (PUSF) as antecedents of usage because numerous research studies have already confirmed the positive impact of PEOU and PUSF on intention to use, e.g. [40-41]. Besides, when we explored impediments of current BI systems, we found that the reason why users supplement their BI system is not primarily a lack of reports and capabilities. Rather, users supplement their BI system because their system is too difficult to use and they cannot find the reports they need. To mitigate this, we proposed a RRA. Therefore, to allow for empirical testing, we now hypothesize that the proposed RRA will improve users' perceived ease of use of the BI system as well as users' perceived usefulness [41]:

> ***H1.*** *A Report Recommendation Assistant which recommends reports based on prior users' social influence has a positive effect on the users' perceived ease of use of the BI system.*

> ***H2.*** *A Report Recommendation Assistant which recommends reports based on prior users' social influence has a positive effect on the users' perceived usefulness of the BI system.*

In addition, we also found that recommendations need to be novel in order to be useful. Otherwise, they might be perceived obstructive. Especially users who already have substantial knowledge about the BI system might prefer a larger share of their screen being dedicated to actual data analysis instead of report recommendations. Therefore, we hypothesize that expertise in using the BI system negatively moderates the RRA's positive impact on perceived ease of use:

> ***H3.*** *A user's expertise in using a certain BI system weakens the positive effect of a Report Recommendation Assistant on that users' perceived ease of use of the BI system.*

4 Research Method

To test the aforementioned hypotheses, we conducted two evaluation studies. First, we conducted a survey to investigate the impact of a RRA on students who have 12 weeks of experience in using the BI system. Second, we conducted a laboratory experiment to investigate the impact of a RRA on BI consultants. This approach allowed for triangulation of the results because novices (i.e., students) as well as experts (i.e., BI consultants) evaluated the RRA. In addition, we conducted semi-structured interviews with some of the BI consultants who participated in the experiment. This allowed us to explore how the proposed RRA should be further refined.

4.1 Confirmatory Studies for Evaluating Design Principle 1

As part of the first evaluation study, 100 graduate students, aged 22-29, who are specializing in "Business Intelligence and Management Support Systems" used a BI system for 12 weeks to explore a retail store's sales data [42]. Students were equipped with and trained in using the aforementioned BI client *SAP BusinessObjects Office Analysis* (Fig. 1) [43]. During the 12 week period, students were using the BI client without a RRA in order to familiarize themselves with the "standard" BI client. Afterwards, we surveyed them about their experienced [40] ease of use and usefulness of the BI client without a RRA. Furthermore, we showed them screen-shots of the BI client with the RRA and asked them about their expected [40] ease of use and usefulness of the BI client with a RRA. Furthermore, we surveyed participants whether they would intend to use the BI client with RRA or the BI client without RRA. All question items were based on the question items of the Technology Acceptance Model [41] because this model and its question items have been validated in numerous studies. Following recommendations in literature [40], question items were only adjusted to capture the difference between experiences and expectations. Finally, we received 98 completely answered questionnaires.

In order to triangulate our findings with experienced BI experts, we selected BI consultants for the second experiment and conducted a scenario description experiment. Scenario description experiments show and describe different scenarios (typically different user interfaces) to participants who then are asked to answer questions about those scenarios. Scenario description experiments are a specific type of laboratory experiments [44]. Since they allow for high control over potential confounding factors (i.e., high internal validity), scenario description experiments are particularly suited as evaluation technique before conducting expensive field experiments [44]. All participating BI consultants worked for one of two large international technology and management consulting companies. Specifically, we provided five BI consultants from each company with a link to the scenario description experiment website who then forwarded the link to further colleagues. Finally, 37 BI consultants answered all scenarios.

The scenario description experiment represented a mixed experiment design with recommendations (on, off) as within-subjects variable and the specific BI client (Tableau Desktop, SAP BW/BO, Microsoft Excel-based BI client) and expertise (self-reported on a Likert scale ranging from 1 to 5) as between-subjects variables. In particular, we first asked participants about their experiences in the usage of the three BI clients. Afterwards we provided four scenarios. Three of those four scenarios showed typical screens of the three BI clients (without RRA) and asked participants about their PEOU of each of them. The fourth scenario randomly selected one BI client, showed a screen of that BI client with a RRA implemented as a side panel (Fig. 1) and asked participants about their PEOU of the shown BI client with RRA. Additionally, in order to focus participant's attention on the shown recommendation assistant, the fourth scenario also included a sentence indicating that the side panel had been added. Again, all question items were adopted from previous literature: three items measuring expertise were adopted from Bhattacherjee and Sanford [45] and four items measuring PEOU were adopted from Davis [41]. Furthermore, to mitigate bias due to carry-over effects, learning effects and decreasing motivation, we counterbalanced the order in which the scenarios were presented to the study participants.

4.2 Subsequent Exploratory Study for Refining Design Principle 1

In order to refine the proposed design principles, we conducted semi-structured interviews with five BI consultants who also participated in the experimental evaluation.

BI consultants were suited for refinement due to their extensive knowledge about organizations' challenges with BI systems. Besides, these interviews also allowed us to qualitatively confirm the experiment findings. Table 1 provides detailed descriptive statistics about the interviews.

During the interviews, we showed the instantiated RRA mockups to the interviewees. Furthermore, we developed an interview guideline which focused on (1) the interviewee's opinion about recommending reports in order to increase reuse of reports, (2) the instantiated interface mockups, (3) ideas for alternative approaches, (4) issues that might occur during a real world implementation of a RRA, and (5) ideas for refinement.

Table 1. Interviews for exploring refinement requirements and opportunities

Interviewee Level	*Quantity*	*Avg. duration*	*Avg. transcript length*
BI Consultant	4	33 min	12 pages
BI Senior Manager	1	54 min	15 pages
Total	5	37 min	13 pages

5 Results

5.1 Confirmatory Evaluation Study 1

First, we compared experienced usefulness and experienced ease of use of the BI client without RRA against the expected usefulness and expected ease of use of the BI client with RRA [40]. Results indicate that both usefulness as well as ease of use are significantly higher with RRA; thus confirming H1 and H2. Table 2 provides detailed statistics. In addition, we asked participants, whether they would prefer to use the BI client without a RRA or with a RRA if they had to choose. On a scale ranging from -3 "strong preference for the BI client without RRA" to 0 "neutral" and to 3 "strong preference for the BI client with RRA", participants on average rated 1.33 (with a standard deviation of 1.19). Therefore, based on the results of this study, we conclude that there seems to be a preference for the BI client with RRA as opposed to the BI client without RRA.

Table 2. Evaluation Study 1: Survey with Graduate Students

Dependent Variable	*BI Client without RRA*	*BI Client with RRA*	*Mean abs. difference*	*t-value*
Perc. usefulness	4.52 (1.15)	5.41 (0.92)	1.09	9.34 ***
Perc. ease of use	4.80 (0.99)	5.23 (1.13)	1.02	10.17 ***

N=98; values in brackets show std. dev.; t-value calculated using paired t-test). Significance levels: ***p<0.001 (two-tailed).

5.2 Confirmatory Evaluation Study 2

To triangulate the first evaluation study's findings, we conducted a second study with BI consultants. We first gathered information about the expertise of participating BI consultants in using the three BI clients. While participants showed similar experiences in using the BI clients *SAP BW/BO* and the *Microsoft Excel*-based BI client, they had less experience in using *Tableau Desktop*. Table 3 provides detailed descriptive statistics on expertise per BI client.

Table 3. Participants' expertise in using the three BI clients

BI Client	*Expertise Mean (Std. dev.)*
Tableau Desktop	2.19 (1.41)
SAP BW/BO	3.32 (1.56)
MS Excel-based BI client	3.22 (1.38)
Total	2.91 (1.26)

Following widespread experiment research [44], we conducted analysis of variance (ANOVA) and F-tests to confirm or reject our hypotheses. As statistical analysis tool we used the statistical programming environment R. Our results indicate that report recommendations have a positive impact on PEOU (H1). Furthermore, our results indicate that the positive effect of report recommendations is reduced by users' prior experience in using the BI client (H3) at $p<0.05$. Although the positive effect of report recommendations on PEOU is "only" significant at $p<0.1$, we view H1 as being confirmed for the following two reasons: First, PEOU increased for all experience levels and all BI clients except for the highest experience level (i.e., experience level 5; see Fig. 3). This indicates that as long as users do not have very strong knowledge about the BI system, a report recommendation assistant increases PEOU. Second, since our evaluation serves as first evaluation cycle, the sample size is rather low and thus moderate significance levels of $p<0.1$ can already indicate interesting effects. Detailed statistics are provided in Table 4.

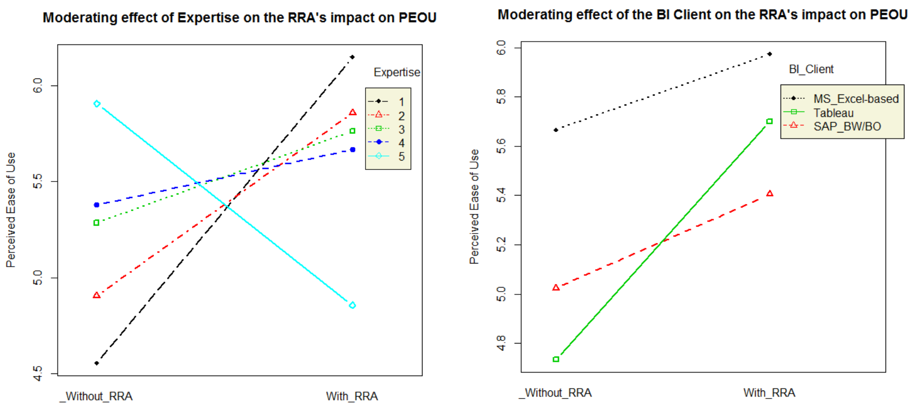

Fig. 3. Moderating effect of expertise (left) and BI client (right) on the report recommendation assistant's (RRA) effect on perceived ease of use (PEOU)

Table 4. Evaluation Study 2: Mixed Design Experiment with BI Consultants

	Df	*Sum Sq*	*Mean Sq*	*F value*	*P(>F)*
Between-subjects:					
Expertise (EXP)	4	0.42	0.106	0.048	0.995
CLIENT	2	6.93	3.464	1.587	0.227
EXP*CLIENT	8	24.23	3.029	1.387	0.256
Residuals	22	48.03	2.183		
Within-subjects:					
Recommendation (REC)	1	4.879	4.879	4.010	**0.058+**
REC*EXP	4	14.629	3.657	3.006	**0.040***
REC*CLIENT	2	0.496	0.248	0.204	0.817
REC*EXP*CLIENT	8	13.952	1.744	1.433	0.238
Residuals	22	26.769	1.217		

Dependent variable: PEOU; N=37. Significance: *p<0.05; +p<0.10
[expertise (EXP); BI client (CLIENT); recommendation (REC)]

6 Refinement and Discussion

In addition to the confirmatory studies, we conducted semi-structured interviews with BI experts in order to refine the proposed RRA. While none of them disputed the results of our evaluation studies, some interviewees raised concerns about the RRA's usefulness for experienced users. For instance, one of them mentioned that it would be *"difficult to find an appropriate algorithm to really suggest something relevant"* (Interviewee 3). According to the interviewed BI experts, the greatest challenge would be the invocation of the RRA – that is, the decision when exactly should a report recommendation be displayed on the user's screen. At first sight, reports may either be suggested to the user upon specific user interactions or constantly through, e.g., a side panel [46]. However, alternatively, the RRA could also be invoked intelligently [47]. This form of invocation fits closest to the opinions of the interviewed BI consultants. For instance, one interviewee argues that recommendations should not be provided constantly or only upon user interactions: *"It's better to blend it in if users do not know something. […] If they know it once, they are not interested in it anymore and would like to have the entire screen for their report." (Interviewee 1)*

Invoking recommendations intelligently (as opposed to constantly or upon user interaction) means that the BI system only recommends reports that are likely to support the user's current task. Instead of being disruptive, the RRA needs to foster the user's engagement in her/his task. Therefore, we draw on recent advancements in *flow* research. The *flow* state has been widely acknowledged for describing an individual's state of being fully focused and engaged in an activity [48]. In particular, if an individual's skills and tasks are optimally balanced, the individual is "in the flow" and performs at the height of her/his skills [48]. Interestingly, recent user experience studies agree on five conditions that improve flow and, thus, should be supported by user interfaces [49-50]: (1) clear perceived goals, (2) unambiguous feedback, (3) a sense of control, (4) a balance between the challenge of the task and skills of the individual, and (5) intrinsic motivation. Since the latter two conditions do not directly refer to the points in time when specific information such as report recommendations should be displayed, we do not consider them for refining the RRA. Furthermore, we assume that a user's sense of control is generally highest if the user is not interrupted with a report recommendation at all. Hence, report recommendations should be avoided in general and should only be displayed if their probability for being helpful is above a pre-defined minimum certainty. As a consequence, we suggest that in order to intelligently provide recommendations and support users' flow state, the BI system should only display recommendations if goals can be supported with a minimum certainty and recommendations are not contradictory among themselves. Specifically, we refine DP1 with the complementary design principles DP1a and DP1b as follows:

> ***DP1a.*** *The BI system should only recommend a report if the goals of the user can be supported with a pre-defined minimum certainty.*

> ***DP1b.*** *The BI system should only provide recommendations that are not ambiguous to other recommendations displayed simultaneously.*

We specifically looked at social influence of prior users as a driver of diffusion. While this is consistent with many research articles, specific types of social influence may be distinguished [31]: 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. Marsden and Friedkin [32] even further 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 [31]. 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 the requirements engineer would gather and describe requirements while the designer would draw mockups. In other words, role equivalence would 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. As a consequence, future research may further refine our RRA by distinguishing between various types of social influence.

7 Conclusion

In this paper, we investigated how to design a BI system that improves diffusion [13] of reports (i.e., reuse of reports across different users) without limiting users' abilities to develop new reports. We built on our previously established DSR project in which we explored four organizations in order to identify impediments to diffusion of reports. Upon identification of impediments, we generalized the need for making social influence of prior report users visible (MR1) and subsequently proposed a RRA which recommends reports based on social influence of prior report users (DP1). Building on this work, in this paper we presented three mockups of the RRA based on different types of BI clients [39] as well as a working prototype. We also developed testable hypotheses in order to be able to evaluate the RRA through empirical confirmation or rejection.

We conducted two quantitative evaluation studies. While the first study focused on graduate students who are specializing in BI, the second study focused on BI consultants. Thus we were able to triangulate findings from novice users with findings from experienced users. The results showed that the proposed RRA improved perceived ease of use and perceived usefulness of the BI client that it extends. Since broad literature confirmed the impact of PEOU and PUSF on employees' usage intentions and ultimately their usage [40-41], [45], we conclude that the RRA increases usage and, thus, diffusion of the recommended reports. However, we did not yet collect longitudinal usage data as part of our evaluations. Thus, in the future, we intend to test diffusion of reports more rigorously by collecting usage data at different points in time in real field settings [13]. Finally, we interviewed BI experts who participated in our experiment. Findings revealed the challenge of recommendation invocation; that is, the decision when to display a report recommendation. To address this challenge, we suggested intelligent invocation of recommendations. Specifically, we draw on *flow* state research and refined DP1 by highlighting that recommendations should only be invoked if they can support the user's goals (DP1a) and if they are not ambiguous to further recommendations (DP1b). Furthermore, insights gained qualitatively confirmed the findings from the quantitative evaluation studies.

Throughout our DSR project we had to make decisions – for instance when deriving meta-requirements from empirical interview findings or when proposing and refining design principles or when instantiating the RRA. We acknowledge that these decisions are not without alternatives. In fact, it is likely that other scholars would have proposed different principles for tackling the identified impediments of current BI systems. Therefore, in order to back our decisions and make our work reproducible, we constantly referred to recent findings in literature. For instance, we focused on improving visibility of social influence in order to increase diffusion of reports because social influence has been widely recognized as a strong driver for diffusion [31], [34]. However, we do neither view our RRA as being "finished" or the only possibility for improving diffusion of reports. Thus, future research should complement and discuss our work. In addition, future research should address the following limitations of our work. First, we investigated BI systems at four organizations. Therefore, studying BI systems in additional organizations might reveal further impediments. Second, DP2 and the refined DP1a and DP1b are still tentative since they are still subjects for evaluation and refinement [20], [25]. Therefore, future work may center on further evaluation and refinement cycles. Third, evaluation study 1 compared experienced PEOU and PUSF of the BI client without RRA with expected PEOU and PUSF of the BI client with RRA. Although this has been done in other studies too [40], those studies mentioned that the two are not always suited for comparison. Therefore, we are currently implementing a RRA in a real organization's BI system and intend to investigate the RRA's impact on actual usage and diffusion over time. Finally, we conducted a scenario description experiment to evaluate DP1. While scenario description experiments allow for high control over potential confounding factors (high internal validity), they typically have little authenticity (low external validity) [44]. Thus, future research should complement our work by examining the impact of DP1 in a real world setting.

References

1. Maas, J.B., Fenema, P.C., Soeters, J.: Information System Infusion: The Role of Control and Empowerment. In: ICIS Proceedings (2012)
2. Györy, A., Cleven, A., Uebernickel, F., Brenner, W.: Exploring the Shadows: IT Governance Approaches to User-Driven Innovation. In: ECIS Proceedings (2012)
3. Baskerville, R.: Individual IS as a Research Arena. Europ. J. Inf. Sys. 20, 251–254 (2011)
4. Behrens, S.: Shadow Systems: The Good, the Bad, the Ugly. Com. ACM 52, 124–129 (2009)
5. Tilson, D., Lyytinen, K., Sørensen, C.: Digital Infrastructures: The missing IS Research Agenda. Information Systems Research 21(4), 748–759 (2010)
6. Davenport, T.H.: Big Data@Work: Dispelling the Myths. Uncovering the Opportunities. HBS Publishing, Boston (2014)
7. Kretzer, M., Gaß, O., Mädche, A.: Design Principles for Diffusion of Reports and Innovative Use of Business Intelligence Platforms. In: WI Proceedings (2015)
8. Bernardes, E., Hanna, M.A.: Theoretical Review of Flexibility, Agility and Responsiveness in the Operations Management Literature. Int. J. Op. Prod. Mgmt. 29(1), 30–53 (2009)
9. Li, X., Hsieh, J.J.P.-A., Rai, A.: Motivational Differences Across Post-Acceptance Information Usage Behaviors: An Investigation in the Business Intelligence Systems Context. Information Systems Research 24(3), 659–682 (2013)
10. Burton-Jones, A., Straub, D.W.: Reconceptualizing System Usage: An Approach and Empirical Test. Information Systems Research 17(3), 228–246 (2006)
11. Farjoun, M.: Beyond Dualism: Stability and Change as a Duality. Academy of Management Review 35(2), 202–225 (2010)
12. Zittrain, J.L.: The Future of the Internet and How to Stop It, New Haven (2008)
13. Rogers, E.: Diffusion of Innovations. Simon and Schuster, New York (2010)
14. Bhattacherjee, A.: Social Science Research: Principles, Methods, and Practices (2012)
15. Attewell, P.: Technology Diffusion and Organizational Learning. Org. Sc. 3(1), 1–19 (1992)
16. Dinev, T., Hu, Q.: The Centrality of Awareness in the Formation of User Behavioral Intention toward Protective Information Technologies. J. AIS 8(7), 386–408 (2007)
17. Mustonen-Ollila, E., Lyytinen, K.: Why Organizations adopt IS Process Innovations: A Longitudinal Study using Diffusion of Innovation Theory. Inf. Sys. J. 13(3), 275–297 (2003)
18. Siponen, M., Pahnila, S., Mahmood, M.: Compliance with Information Security Policies: An Empirical Investigation. IEEE Computer 43(2), 64–71 (2010)

19. Gregor, S., Hevner, A.R.: Positioning and Presenting Design Science Research for Maximum Impact. MIS Quarterly 37(2), 337–355 (2013)
20. Kuechler, W., Vaishnavi, V.: A Framework for Theory Development in DSR: Multiple Perspectives. J. AIS 13(6), 395–423 (2012)
21. Gill, T.G.: Reflections on Reshaping the Rugged Fitness Landscape. Int. J. Emerging Transdiscipline, 165-196 (2008)
22. Carlsson, S.A.: DSR in IS: A Critical Realist Approach. In: Hevner, A., Chatterjee, S. (eds.) Design Research in IS, pp. 209–233. Springer (2010)
23. Goes, P.B.: Design Science Research in Top IS Journals. MIS Quarterly 38(1), ii-viii (2014)
24. Nunamaker, J., Derrick, D., Elkins, A., Burgoon, J., Patton, M.: Embodies Conversational Agent-Based Kiosk for Automated Interviewing. J. Mgmt. Inf. Sys. 28(1), 17–48 (2011)
25. Hevner, A.R.: A Three Cycle View of DSR. Scand. J. Inf. Sys. 19(2), art. 4 (2007)
26. Day, J.M., Junglas, I., Silva, L.: Information Flow Impediments in Disaster Relief Supply Chain. J. AIS 10(8), 637–660 (2009)
27. Walls, J.G., Widmeyer, G.R., El Sawy, O.A.: Assessing IS Design Theory in Perspective. JITTA 6(2), 43–58 (2004)
28. Myers, D.M.: Qualitative Research in Business & Management. Sage Publications (2009)
29. Lapointe, L., Rivard, S.: A Triple Take on Information Systems Implementation. Organization Science 18(1), 89–107 (2007)
30. Unger, C., Kemper, H.-G., Russland, A.: Business Intelligence Center Concepts. In: AMCIS Proceedings (2008)
31. Singh, P.V., Phelps, C.: Networks, Social Influence, and the Choice Among Competing Innovations. Information Systems Research 24(3), 539–560 (2013)
32. Marsden, P., Friedkin, N.: Network Studies of Social Influence. Social Methods Research 22(1), 127–151 (1993)
33. Angst, C., Agarwal, R., Sambamurthy, V., Kelly, K.: Social Contagion and Information Technology Diffusion. Management Science 56(8), 1219–1241 (2010)
34. Fichman, R.G., Dos Santos, B.L., Zheng, Z.E.: Digital Innovation as a Fundamental and Powerful Concept in the IS Curriculm. MIS Quarterly 38(2), 329–354 (2014)
35. Silver, M.S.: Decisional Guidance for Computer-Based Decision Support. MIS Quarterly 15(1), 105–122 (1991)
36. Dhaliwal, J.S., Benbasat, I.: The Use and Effects of Knowledge-based System Explanations. Information Systems Research 7(3) (1996)
37. Limayem, M., DeSanctis, G.: Providing Decisional Guidance for Multicriteria Decision Making in Groups. Information Systems Research 11(4), 386–401 (2000)
38. Zhang, T., Agarwal, R., Lucas, H.C.: The Value of IT-Enabled Retailer Learning. MIS Quarterly 35(4), 859–881 (2011)
39. SAP. SAP BusinessObject BI Clients (2013), `http://tinyurl.com/lmvaj7o`
40. Brown, S.A., Venkatesh, V., Goyal, S.: Expectation Confirmation in Information Systems Research. MIS Quarterly 38(3), 729–756 (2014)
41. Davis, F.D.: Perceived Usefulness, Perceived Ease of Use, and User Acceptance of IT. MIS Quarterly 13(3), 319–340 (1989)
42. Microsoft: Contoso Retail Store Business Intelligence Dataset (January 01, 2015), http://microsoft.com/en-us/download/confirmation.aspx?id=18279
43. SAP: SAP BusinessObjects Analysis, edition for Microsoft Office (January 27, 2015), http://scn.sap.com/community/businessobjects-analysis-ms-office
44. Homburg, C.: Marketingmanagement, 5th edn. Springer, Gabler (2014)

45. Bhattacherjee, A., Sanford, C.: Influence Processes for Information Technology Acceptance. MIS Quarterly 30(4), 805–825 (2006)
46. Silver, M.: Decisional Guidance: Broadening the Scope. Advances in Management Information Systems 6, 90–119 (2006)
47. Gregor, S., Benbasat, I.: Explanations from Intelligent Systems: Theoretical Foundations and Implications for Practice. MIS Quarterly 23(4), 497–530 (1999)
48. Csikszentmihalyi, M.: Flow: The Psychology of Optimal Experience, New York, NY (1990)
49. Hamari, J., Koivisto, J.: Measuring Flow in Gamification: Dispositional Flow Scale-2. Computers in Human Behavior 40, 133–143 (2014)
50. Procci, K., Singer, A.R., Levy, K.R., Bowers, C.: Measuring the Flow Experience of Gamers. Computers in Human Behavior 28(6), 2306–2312 (2012)