BI-FIT: The fit between Business Intelligence end-users, tasks and technologies

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Abstract: This paper aims at investigating the factors that influence the "fit" between Business Intelligence (BI) end-users, tasks and technologies (BI-FIT). Based on an extensive literature study on the elements of BI-FIT, in this research a BI end-user segmentation model is developed that shows the most relevant factors and the interrelationships between BI end-users, tasks and technologies. This model can be used to help organizations to identify and fulfill the needs of BI end-users, thereby improving adoption and increasing satisfaction of the BI end-user base. The BI-FIT model is evaluated empirically through a multiple case study to enrich and validate the theory.

Keywords: Business Intelligence; End-user segmentation; Adoption; Task-Technology FIT.

1. Introduction: the information gap

In today's globalized economy ―especially during times of recession― the uncertainty that organizations are facing when taking decisions has become bigger. In order to deal with this uncertainty, organizations process information (Daft & Lengel, 1986). According to Galbraith (1974, p. 28) "the principle of a managerial task is to reduce uncertainty by processing information." The demand for profits, increasing (global) competition, and demanding customers all require organizations to take the best decisions as fast as possible (Vitt, Luckevich, & Misner, 2002). Therefore, the ability to quickly take advantage of the exponential growing amount of information has become an extremely critical component for the success of the modern organization (Barlow & Burke, 1999; Huber, 2003). The need for fast decision making on the one hand, and the longer time needed to acquire the right information on the other hand causes a so-called "information gap" (den Hamer, 2005; van Beek, 2006). Business Intelligence (BI) is implemented in order to narrow down this information gap.

1.1. Problem definition

Over the years BI has increasingly been moving into the mainstream of knowledge worker computing (Negash & Gray, 2003). No longer are BI solutions solely being used by information specialists or analysts. This is reflected in the population of BI-end users, which is becoming increasingly more heterogeneous in both the skills that end-users bring to BI-systems as well as in the demands they place on them (Gile, 2003). Unfortunately, according to several authors many BI projects fall short of their promise to deliver value. According to Raden (2004, p. 10), "business intelligence applications have low adoption rates within organizations". Furthermore, Biere (2003, p. 8) states that "too many organizations take the easy technology-driven route by selecting some tools, hoping the end users will "magically" emerge with what they want." Finally, Ferguson (1996, p. 13) states that "less attention is devoted to actual BI usage on the problem of getting data out of the system. This approach has diminished the potential benefit of BI systems since it assumes that all users are capable of finding their way around in this 'ocean' of information." In other words, an implementation from a technology-driven perspective does not ensure the adoption and usage of end-users, which constrains organizations to benefit from the potential of their BI investments.

Looking from an end-users perspective, end-users simply want a better way to solve data-related business problems. The end-user's perception of the benefits received from a BI solution is dependent on the degree of productivity increase or the amount of positive results that they receive. If a BI solution helps them look better, and lets them do their job better, they will be more likely to use it (Turban et al., 2007). While BI-software enables organization-wide decision support, problems are encountered in the fit between systems' provision and changing requirements of a growing amount of (end-) users (Dekkers, Versendaal & Batenburg, 2007). The main reason why this "fit" (hereafter referred to as BI-FIT) is missing is that when BI-solutions are implemented in practice, end-users are usually considered (if considered at all) to be equal in their adoption and usage of the system (Biere, 2003), which is not always the case (Borgman, 1989). If end-users get provided with a BI-solution that does not fit their capabilities or tasks, they will most likely not use it, or use it in the wrong manner, or even become negative about the BI-solution, which obviously does not contribute to a positive result. However, if end-users are equipped with a BI-system that fits their needs, they will produce better intelligence to support their decisions, and in the end reduce uncertainty. In order to establish this fit, this paper develops a model which provides an answer to the following research question:

"What are the major factors influencing the fit between Business Intelligence end-users and Business Intelligence solutions?"

1.2 Research motivation and methodology

Although BI is widely applied in practice, scientific research in the field is limited. Several authors state that BI research "seems to have flown under the radar of academics" (Negash & Gray, 2003; Pirttimäki, Lönnqvist, & Karjaluoto, 2006). Most available literature focuses on BI technology such as data-warehousing (Barbara, Wixom, & Watson, 2001; Kimball, 2008), OLAP (online analytical processing)

(Chaudhuri & Dayal, 1997; Tremblay et al., 2007) and data-mining (Fayyad & Uthurusamy, 1996; Han & Kamber, 2006). Unfortunately, considerably less attention is given to the organizational side of BI, investigating BI processes and BI organization (Philips & Vriens, 1999; Pirttimäki & Hannula, 2003; Zeng, Xu, Shi, Wang, & Wu, 2006a). By investigating BI-FIT, this paper provides new insights into research on the organizational aspects of BI as well as a better understanding of BI end-user adoption.

In general, the goal of Information Systems (IS) research is to produce knowledge that enables the application of information technology for managerial and organizational purposes (Hevner, et al., 2004). The main goal of this research is to develop a model that depicts the major factors influencing BI-FIT, which can be used to assist organizations in identifying and defining differing BI end-user groups and their needs, in order to provide end-users with a BI solution that fits. For this purpose, a design research approach is used. By means of constructing an artifact, new scientific knowledge can be generated (Hevner et al., 2004; Vaishnavi & Kuechler, 2007). In this research the artifact is the BI-FIT model, which is developed according to the steps (problem awareness, suggestion and development, evaluation & conclusion) in developing design research artifacts as described by Vaishnavi et. al. (2007). Awareness of the problem area was raised in discussions with BI practitioners from the field, BI literature reporting BI success and failure, and in articles in in BI professional magazines and blogs. A detailed problem description was provided in section 1.

Based on the problems as described in section 1 it has become clear that when implementing BI, more time and attention need to be devoted to the actual end-users of the BI solution, instead of purely focusing on technology. However, because limited knowledge on BI end-user adoption is available, it was decided to investigate the main factors influencing BI usage from an end-users perspective as described in section 3. Furthermore, the factors identified are used to develop a BI end-user segmentation model which can be used to assist organizations in providing their end-users with a BI-solution that fits their needs, as described in section 4. The segmentation model has been evaluated by carrying out a multiple case study within six organizations, following Yin (2008; 2003). Hevner et al. (2004) also suggest case studies as an appropriate evaluation method in design research. Results of the case studies are discussed in section 5. Finally, section 6 contains conclusions and suggestions for further improvement.

2. End-User FIT

The relationship between investment in information technology (IT) and its effect (IT-impact) on organizational performance is a major area of interest for (IS) researchers and practitioners. It must be clear that it is not the investment in technology that is the driver for IT impact, but the actual usage of the technology (Devaraj & Kohli, 2003). Persuading end-users to adopt information technologies persists as a major challenge confronting those responsible for implementation. An important question in this context is: What causes individual end-users to adopt new information technologies, and in particular BI-systems? The term “individual” is used explicitly because this research starts from the observation that the growing amount of BI end-users are heterogeneous, both in the skills they bring to BI-systems and the demands they place on them (Gile, 2003). The same IT-system can be seen as successful by one individual end-user or group but as a failure or at least problematic by another end-user or group (Agarwal & Prasad, 1999). Several interconnected factors seem to influence this.

2.1. Factors influencing Adoption / Utilization

In literature several models have been proposed that intend to explain the factors that influence end-users IT adoption and utilization and therefore explain IT success or failure. The Information Success Model (ISM) developed by Delone and Mclean (1992) was a breakthrough because they proposed a model to asses IS from the end-users' perspective. Basically, the ISM suggests that system quality and information quality determine IT success. However, among others Davis (1993) criticizes the ISM model by stating that quality is not the only factor determining success, and has developed the Technology Acceptance Model (TAM). The TAM has been proposed to explain the factors that influence an end-users decision to utilize a system or not, and is a widely cited model in IS research. Basically, the TAM defines the constructs "perceived ease of use" and "perceived usefulness" to predict an end-user's attitude towards using and actual system use (Davis, 1993). Both factors themselves are influenced by so-called "external factors" like for example individual characteristics of end-users or IT-system characteristics. Although the TAM is a widely cited model, it is criticized concerning its "lack of task focus", because it does not take into account that end-users use IT even if they do not like it, simply because it improves their job performance (Goodhue & Thompson, 1995). Furthermore, one of the main properties of the TAM, is that it is designed for voluntary use of IS systems (Davis, 1993), which is not always applicable.

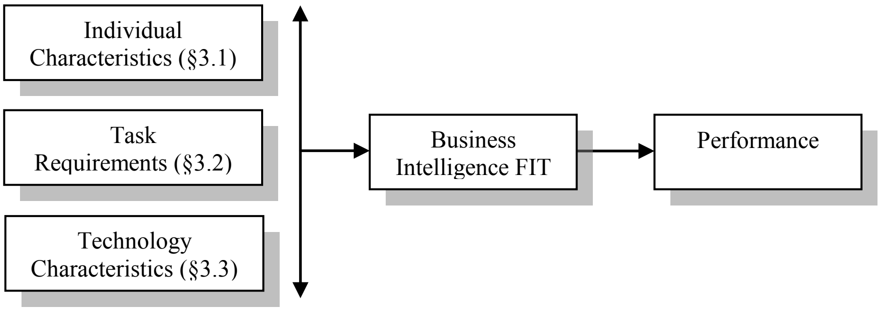
In response to the critique on existing IT acceptance models, Goodhue & Thompson (1995) developed the Task-Technology-Fit model (TTF). The 'fit' is explained as "the extent to which technology functionality matches task requirements and individual abilities" (Goodhue & Thompson, 1995, p. 216). In other words, "the TTF posits that IT systems will be used if, and only if, the functions available to the user support (fit) the activities and individual capabilities of the user" (Dishaw & Strong, 1999, p. 11). Furthermore, the TTF model has proven that not only the individual factors (individual characteristics, task characteristics, technology characteristics) are important, but also the quality of the "fit" between them. To conclude, the discussion of IS acceptance models has learned us that several interrelated factors influence BI adoption and usage. An overview is depicted in table 1.

Table 1: Overview of IS acceptance models

Authors	Model	Factors influencing adoption
Delone & Mclean (1992)	Information Success Model	System and information quality.
Davis (1993)	Technology Acceptance Model	Individual end-users "perceived usefulness, and perceived ease of use."
Goodhue & Thompson (1995)	Task – Technology– Fit Model	Fit between Individual -, Task- & Technology characteristics.

Based on the TTF model, the BI-FIT model is proposed, which depicts the main factors that influence the fit between BI end-user and solutions. The BI-FIT model is included in figure 1. Adopted from the TTF model, the BI-FIT model assumes that a high degree of "BI-FIT" has a positive effect on adoption, which positively influences performance and a low degree of "BI-FIT" has the opposite effect. Since the BI-FIT is considered to be dynamic, and therefore should be monitored because of changes over time in individual, task or technology characteristics. This research does not employ the TTF model as an instrument to measure constructs, but rather to contribute to a better understanding of the interrelationships between and consequences of BI-specific individual, task and technology characteristics.

Figure 1: BI-FIT Model, based on the TTF model (Goodhue & Thompson, 1995)



3. BI-FIT Framework

One of the main objectives of any BI-implementation is to meet the diverse needs of a diverse set of end-users. Therefore, the first requirement is to understand "who" the end-users are in order to determine "what" they need (Gile, 2003). As discussed above, end-users are not equal, and therefore have different requirements. Unfortunately, in most cases it is not possible to develop a customized solution for each individual end-user. Therefore, there is a need for segmentation, in order to understand the needs of the different user constituencies within the BI end-user community, since each has a different set of requirements and preferences. Based on the factors that influence the BI-FIT which were discussed above, a BI end-user segmentation model is developed which is described in the remainder of this paper.

3.1. Individual Characteristics

Individuals within an organization need the ability to perform their task efficiently by applying information technologies and systems to their work , also defined as end-user computing competency (Yoon, 2008, p. 415). Several studies have examined acceptance and usage of BI or related systems (DSS, EIS, ESS, MIS etcetera) focusing among others at individual characteristics, and have identified computer proficiency (also named IT know-how, computer experience, IT skills) and analytical capabilities as influencing factors (Agarwal & Prasad, 1999; Dixon, 1999; Hung, 2003; Pijpers et al., 2001; Seeley & Targett, 1999; Taylor & Todd, 1995). A BI end-user with a high computer proficiency is more likely to successfully use advanced BI-tool functionalities and contrariwise. The same applies for analytical capabilities. For example, the degree of computer proficiency and analytical abilities required to understand and draw conclusions based upon a simple report is quite different from the capabilities necessary to create a customized report.

Therefore, computer proficiency and analytical capabilities, are used to classify BI end-users focusing on their individual characteristics, by dividing them into three groups: Novice, Power and Expert end-users, as depicted in Table2. In addition, end-users are divided based upon whether they solely consume or also produce information. The reasoning behind this is that some end-users will take a hands-on approach to tools and data, while others wait for finished analysis and reports. One is oriented to the analytics, while the other just wants the resulting information (Biere, 2003). Therefore, novice users are classified as information consumers, and power and expert users are as information producers.

3.2. Task Requirements

In addition to individual characteristics, as discussed above , an end-users decision to adopt and use a system also depends on whether it enhances or "fits" the end-users' task. Tasks have been broadly defined as the action(s) carried out by an individual for turning inputs into outputs (Tremblay et al., 2007). End-users use BI-systems to get relevant information which helps them to reduce uncertainty when taking decisions, and enables them to make decisions based on a solid foundation of facts (Nemati et al, 2002). Since the details of business decisions are quite different for each organization, level (i.e. operational, tactical, or strategic), process and user-task context, it is not possible to investigate task requirements for every specific decision task to be supported within an organization.

However, it is possible to examine what BI end-users expect to get out of BI applications, not specifically looking at the content but by examining how and in what way end-users want to interact with information. According to several authors (Haller, Jenichl, & Küng, 1998; Nemati et al., 2002; Wong et al., 2002), the various ways of processing information can separated into two "modes": Verification mode and Discovery mode. In verification mode the user proposes a hypothesis (e.g. business questions) and uses the information to either confirm or reject it, whereas in the discovery mode the end-user does not use a predefined hypothesis, but desires to discover new information, without preconceived notes of what the results would indicate (Fayyad & Uthurusamy, 1996). According to Azvine et al. (2006), the analytical needs of business end-users all come down to answering the following three questions, sorted by ascending complexity:

- What has happened?
- Why did it happen?
- What will happen?

Simple or routine analysis is conducted to answer the often recurring "what happened" question (verification mode) and if exceptions are found, less frequent occurring ad-hoc analysis is conducted to try to answer the more complex "why" question (verification mode). Future oriented analysis aims to figure out "what will happen" (discovery mode) is considered to be the most advanced type of analysis. In addition, data usage and distribution seem to be influenced by the complexity of the analytical question. For example: Routine analysis is often recurring daily, weekly or monthly, usually presented in standardized preformatted reports which are often "pushed" to end-users by e-mail or other electronic distribution means whereas when carrying out less regular ad-hoc analysis or advanced analysis, end-users actively use the system to fetch or "pull" their required data for analysis, which varies along the nature of the analytical question. As depicted in table 2, analytical tasks are divided into routine, ad-hoc and advanced analysis tasks, based on their analytical complexity, data distribution, and variation in data usage.

3.3. Technology Characteristics

As discussed earlier, organizations have huge amounts of detailed operational data, usually spread across many departments in the organization or locked into a sluggish operational IT environment, which keeps business decision makers from getting the right information in time (Zeng et al., 2006b). This is demonstrated by the following statement: "I know the answer to my problem is hidden in my data… But I cannot dig it up!!" (Michalewicz et al.,2007, p. 1). Therefore, the most important aspect of most BI projects, is "to provide the best possible mechanism for information delivery to business end-users". To make this happen, organizations can choose from a broad spectrum of BI front-end functionality (also referred to as analytics) ranging from (simple) predefined reporting to (advanced) data-mining tools to fulfill their analytical needs (Breitner, 1997).

According to den Hamer (2005), the selection of the appropriate BI instrument strongly depends on the type of question that needs to be answered varying from simple 'what' to complex 'why' questions. This is supported by Azvine et al. (2005) who states that data-analysis tools can be categorized looking at their ability to support end-users in fulfilling their analytical needs (as defined in section 4.2). Furthermore, as the analysis becomes more complex, the required BI functionality also places a higher demand on end-users' abilities. Based on their purpose and complexity, BI tool functionality can be classified into three categories: Basic, Root-cause and Advanced analytics, as depicted in table 2.

3.4. BI end-user segmentation model

Multiple groups of business end-users, within different skills, preferences and tasks throughout the organization spread among various organizational levels use BI tools to facilitate their decision making processes. Unfortunately, business end-users —while being experts in their area— do not necessary possess expert skills in data analysis (Kohavi, Rothleder, & Simoudis, 2002; Nauck, Spott, & Azvine, 2003). Therefore, the BI end-user segmentation model, as depicted in table 2 has been developed in order to assist organizations fulfilling their end-users needs. It is important to note that there may not be a relationship between the end-users" skills (abilities) and organizational position (i.e. operational, tactical, strategic). Obviously, there is no doubt whether a expert end-user is able to deliver added value, but it is not necessarily the case that an end-user with a better ability to use BI systems will have a bigger impact on business (Biere, 2003).

The BI end-user segmentation model , depicted in table 2, shows a "fit" between end-users' individual capabilities, tasks and technologies on the horizontal rows of the model. For example, a novice user carries out routine analyses, using basic analytical tool-functionalities. A "fit" can also exist when a power user carries out a routine analysis, using basic tool functionality, but only if the power users is also provided with root-cause analytics to conduct further analysis if exceptions are found. However, this is not possible the other way around. An important question in this context is: What happens if a novice user finds an exception and is required to do further analysis? This is an example of a "misfit" between end-users individual capabilities and task. According to the model the novice user does not possess the required capabilities to do so, therefore no "fit" exists. In this case two options are possible. The first option is that the novice user contacts a power user, and asks the power user to do the extended analysis. The second option is to educate the novice user, in order to become a power user, if the novice user has a regular need for further analysis.

A "misfit" can also exist between task and technology. Consider an expert end-user who needs to conduct an advanced analysis, like e.g. data-mining, but is not provided with the required tools. In this case the user will feel limited in his or her possibilities, and will not adopt the BI-solution, and probably start searching or developing alternative solutions. To conclude, the BI segmentation model is the result of an extensive literature study on the elements of BI-FIT. It shows the most relevant factors and the interrelationships between BI end-users, tasks and technologies. Having discussed the problem awareness and suggestion and development phase of the research approach (see chapter 2), the next step in the research is to evaluate the theory in practice.

4. Evaluation of the BI-FIT model: Multiple case studies

Focusing on the problem area of this research, use cases seem an appropriate choice of research method, because case study research is well suited for organizational issues rather than technical issues (Yin, 2008). This also applies to this research, which investigates problems of organizational nature. The case study research method is applied in this research to capture the knowledge of practitioners and to validate the theories created. In order to enrich and validate the theory created with experiences from practice, it is investigated how organizations deal with differing BI end-users and the factors influencing of BI-FIT, by identifying and comparing the end-users' constituencies and their BI usage in the case organizations with the BI segmentation model. In addition the elements of the model are validated by discussing the relevant segmentation criteria used to distinguish BI end-users. Despite the fact that all individual cases are interesting, this chapter focuses on the overall results.

Table 2: BI End-user segmentation model

End-user				Task				Technology		
Definition	Computer proficiency	Analytical capabilities	# Users	Definition	Distribution mechanism	Data-demand	Analytical complexity	Definition	Techn. complexity	BI- Tool Functionality
Novice Users (information consumer)	Low	Low	High	Routine Analysis	Push	Static	Simple	Basic Analytics	Simple	Preformatted reporting , Parameter-driven reporting, Scorecards, Dashboards
Power Users (information producer)	↕	↕	↕	Ad-Hoc Analysis	↕	↕	↕	Root-cause Analytics	↕	Ad-Hoc reporting, Online analytical processing (OLAP)
Expert Users (information producer)	High	High	Low	Advanced Analysis	Pull	Dynamic	Complex	Advanced Analytics	Complex	Data-mining, Advanced statistics, (predictive / historical), Simulation.

4.1. Case organizations

The case studies have been conducted at larger organizations of differing sizes, operating in several types of industries, and offering a wide variety of products and services. The main criterion in our search for suitable organizations was that all approached organizations have a professionally implemented BI system in place. Important criteria for selecting respondents per case were that the cooperating respondents had an overall view of BI usage in their organization and that they had been actively involved during the implementation. To increase the validity of the results, triangulation is applied because multiple respondents have been interviewed per case and in addition to interviews also documentation was studied. An overview of the case study organizations and respondents is provided in table 3&4.

Table 3: Case Overview (figures taken from 2008 annual reports)

Organizations	A	B	C	D	E	F
Type / Branch	Electronics	Transport	Food & Beverages	Non - Profit	Telecom-munications	Transport
Market	B2B & B2C	B2B	B2B & B2C	G2C	B2B & B2C	B2B
Revenue € (million)	26.385	3.5	485	112	14.602	1.330
# Employees	+/ - 120.000	+/ - 100	+/ - 2.900	+/ - 550	+/ - 40.000	+/ - 2.750
BI front-end tool	SAP BW	Microsoft Reporting	SAP BW	Business Objects	Cognos	Webfocus
# BI End-users	+/ - 250	+/- 20	+/- 700	+/ - 250	+/- 1500	+/- 100

Table 4: Respondent overview

Organizations	A	B	C	D	E	F
Respondent 1 Function	Project manager	BI consultant	BI consultant	BI consultant	BI manager	BI manager
Respondent 1 project –role	BI project manager	Project manager / analyst	Developer / analyst	BI project manager	BI manager	BI manager
Respondent 2 Function	Key-user F&A	BI Consultant	BI manager	BI support	NA	BI support
Respondent 2 project-role	Key-user	BI Developer	BI manager	Functional support	NA	Functional / technical support

4.2. Validation of the segmentation criteria

After introducing the research topic, all interviewees responded to have recognized the problem area, and stressed the importance of end-user adoption. Furthermore, there was consensus about the fact that especially when a high amount of end-users needs to be addressed, end-users cannot be satisfied with a ‘one size fits all solution’. Next, after discussing the main assumptions and elements of the BI-FIT model, respondents were asked to identify the relevant individual characteristics applicable for BI. It appeared that in addition the above discussed computer proficiency and analytical abilities, most respondents consider process knowledge, as an important capability of BI end-users. So basically when conducting analysis using BI tooling, an end-user must know how-to analyze (analytical capabilities), how-to use the tool (computer proficiency), and must also posses knowledge of the business process that is analyzed, in order interpret the outcome of the analysis, and to be able to understand the impact on the business. Furthermore, as the complexity of the analysis goes up, a more profound business knowledge is required. Therefore, business knowledge seems like a plausible contribution to the model.

4.3. Findings – BI usage in practice

While investigating the case organizations’ end-user communities it appeared that in some organizations an explicit end-user segmentation model had been developed, while others had not explicitly done so. In the case of organizations A and C, end-users are explicitly divided into groups, and it appears that next to the purpose of segmenting end-users, as discussed in Section 3, such as establishment of the end-user fit, other purposes of end-user segmentation are to ensure a flexible reporting process (because of the responsibility of the “power” user, as discussed below), and to select the appropriate form of training, as e.g. novice users require different training than expert users.

It appears that in each organization explicitly or implicitly —after some time of BI usage— end-user groups are formed, which in general can be compared to the end-user types as defined in the model, although using different terminology. An overview of the used terminology is depicted in table 5. In addition to terminology differences in practice an additional level of BI usage exists, as found in organization A, C and E. These end-users are defined as “receivers” or “consumers”, conducting solely routine analysis, using predefined reports, in most cases send out by e-mail. The main difference between receivers and novice users is that they are not required to have any BI tool/computer proficiency, do not require tool training, and tool license (or a cheaper license, depending on the BI-tooling). In the segmentation model these end-users belong to the group of information consumers, and are placed above the novice user, as entry level BI users.

Table 5: Terminology Overview

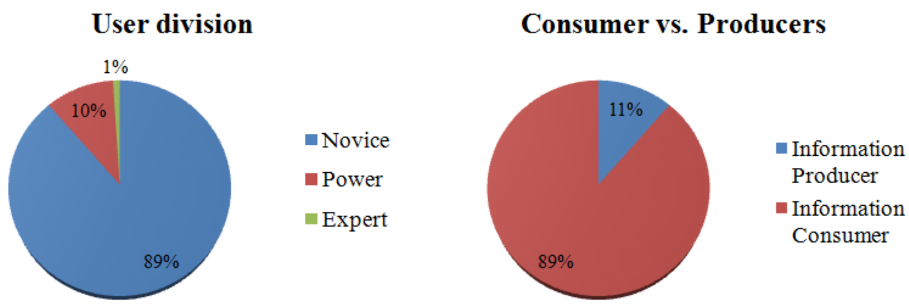
User Segments	Terminology
Novice User	Information consumer, Knowledge worker, Manager, Receiver,
Power User	Power user, Analyst, Business user, Tactical user
Expert User	Expert user, Data-miner.

Furthermore, an interesting finding is that the power user has an important role, which is to support the novice user. In most organizations novice users are by far the largest amount of end-users. While conducting their standard analysis, it often happens that the novice user is in need for further analysis or has a request for change. As explained earlier, in this case the novice user can obviously consult an analyst of the BI department or competency centre (BICC) in place. However, as in most cases BI support is integrated into the generic IT departments, usually it takes a long time for change requests to be handled (as IT departments are often optimized for supporting operational systems). If this happens more often, the novice user will lose his or her trust in the system, and stop using it and start developing his or her own solution in e.g. Excel. Or maybe even try to adapt the reports themselves, if they have access to the required tooling. Either way, ad-hoc development is not efficient in general, and abandoning of the BI system does not positively influence organizational results.

However, as one of the respondents stated "a change in today's business, needs to be reflected in tomorrow's reports". This basically means that BI requires a flexible and quick requirements process. Therefore, it is important to have a substantial amount of power users in each process, that can assist novice users. Especially, because in addition to the required tool and analytical skills, power users also possess the required business knowledge (in contrast to organization wide BI support) in order to support the novice users in their process. Therefore, power users play an important role to ensure the required flexibility of the BI process. In addition to the above findings, it was also investigated how many end-users are present in each segment. Figure 2 shows that the focus is largely on novice usage (i.e. information consumers) with considerably less power users and hardly any expert users. Although it was expected to have less power and expert users, because of the higher demands placed on their individual capabilities, especially the power user group was expected to be bigger. Furthermore, following Negash and Gray (2003) most BI tooling focuses on the power user. Perhaps this is a signal for BI vendors to start developing tooling that aim at bringing more analytical functions to novice users. However, obviously we must be aware that not only the ability to use a tool can help to make an end-user a good analyst, also the analytical abilities and business knowledge are important.

Another interesting finding is that hardly any expert users were around. This could mean that organizations are not making use of the full potential of BI, since advanced analysis often brings valuable results. To conclude, in order to benefit from the potential of the available data in an organization, and to ensure a flexible BI process it is important to be able to include a substantial amount of power users in each process, and a relatively few expert users to fully benefit from the possibilities of BI technology.

Figure 2: Division of end-users



5. Conclusions

This research has identified the main factors influencing a BI end-users choice to adopt and use a BI solution or not. For an end-user to adopt BI, it is important that a "fit" is established between the BI end-user and the BI solution. The end-user fit can be established by making sure that end-users are provided with a solution that matches their individual characteristics, and provides added value in task execution. The BI end-user segmentation model has been developed in this research, to support organizations in establishing this fit. It can be used to help organizations to identify and fulfill the needs of end-users, thereby improving adoption and increasing satisfaction of the BI end-user base.

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