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Business Intelligence & Analytics (BI&A) Systems

Measuring End-User Computing Satisfaction (EUCS)

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Business Intelligence & Analytics (BI&A) systems: measuring End-User Computing Satisfaction (EUCS)

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Abstract: Business intelligence and analytics (BI&A) have become part of almost every company/organisation nowadays, as the benefits of a successful adoption are many. However, the failure scenarios are many as well, with companies/organisations facing dissatisfied employees who do not use the BI&A tools because they find them difficult to use -despite the trainings-, and others who start using them and then stop this usage. In an effort to help companies/organisations who want to adopt or have adopted a BI&A solution to understand their employees, as well as BI&A vendors to understand their end-users, we conducted this study where we examined the relationships among training, system usage, EUCS and UCI. What is more, we decided to focus only to descriptive BI&A as it is the type of BI&A that is mostly adopted by companies/organisations. The data needed for the study was collected with the help of a questionnaire-based survey and four hypotheses were developed for our literature-based proposed model. Data analysis was conducted with Excel, SPSS and AMOS and all of our hypotheses were confirmed. This is a sign that companies/organisations should keep investing on training in order to achieve higher levels of BI&A usage and eventually higher levels of EUCS and UCI.

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Georgia Antoniou, Nikolina Papoglou

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Table of abbreviations

Terms	Definitions
BI	Business Intelligence
BA	Business Analytics
BI&A	Business Intelligence and Analytics
DSS	Decision Support System
ETL	Extract-Transform-Load
OLAP	Online Analytic Processing
IS	Information Systems
IT	Information Technology
EUC	End-User Computing
EUCS	End-User Computer Satisfaction
UCI	Usage Continuance Intention
TAM	Technology Acceptance Model
D&M	DeLone and McLean
MIS	Management Information System
ERP	Enterprise Resource Planning
HIS	Hospital Information System
CAS	Computerised Accounting System
LTC	Long-term care

1 Introduction

1.1 Background

Business Intelligence (BI) software is a group of different technological tools aimed at helping organisations in decision making (Chaudhuri, Dayal, & Narasayya, 2011). BI, which was introduced as a term in the 1990s (Chen, Chiang, & Storey, 2012), has been around for many years with different names, like Decision Support System (DSS) and Management Information System (MIS) (Olszak & Ziemba, 2012; Thomsen, 2003).

Nowadays, BI represents a combination of processes, technologies and tools (Shariat & Hightower, 2007). This combination aims at transforming raw data into meaningful information and information into knowledge, something excessively important in a world where Big Data is getting even bigger day after day (Mayer-Schönberger, & Cukier, 2013). The transformation is supported by BI systems that gather, store and process data (Chaudhuri et al., 2011).

Therefore, a typical BI system involves an Extract-Transform-Load (ETL) tool, a data warehouse server which manages a database and an Online Analytic Processing (OLAP) server (Chaudhuri et al., 2011). The final product is presented to the end-user though front-end applications such as spreadsheets, ad-hoc queries or dashboards (Chaudhuri et al., 2011).

In the late 2000s, a new term called Business Analytics (BA) emerged (Chen et al., 2012). BA is focused on the analytical component of BI (Chen et al., 2012). However, nowadays the two terms are unified since BI and BA are complementary to each other (Corte-Real, Oliveira, & Ruivo, 2014). Therefore, for the rest of the paper, we will use the term BI&A, which has also been used in previous studies (Chen et al., 2012; Corte-Real et al., 2014). According to the decision that has to be made, BI&A is divided into three categories: 1) descriptive, 2) predictive and 3) prescriptive (Evans, 2012). Descriptive BI&A is applied to describing what has happened, predictive BI&A helps in making predictions based on historical data while prescriptive BI&A is about optimization, as it helps in finding the best possible solution (Evans, 2012).

In spite of its usefulness, it has been only for the last two decades that BI&A software has become extremely popular among enterprises (Chaudhuri et al., 2011) something which is logical if we also take into consideration the increase in the use of PCs during this period. Gartner's survey (2013) confirms this, as BI&A appears to be the number one CIOs' technological choice for 2012 and 2013.

This rise in the popularity of the BI&A software is completely justified. The openness of the economies has brought the markets face-to-face with a situation of fierce competition (Søilen, 2012). Apart from that, companies/organisations have to deal with the Big Data and manage the so-called three V's:1) volume, 2) velocity and 3) variety (McAfee & Brynjolfsson, 2012). Consequently, companies/organisations, regardless of the industry sector in which they operate, do adopt a BI&A solution in order to solve these problems and achieve competitive advantage (Sharma, Reynolds, Scheepers, Seddon, & Shanks, 2010). Hospitals (Aggelidis & Chatzoglou, 2012), police departments (Tona, Carlsson, & Eom, 2012), retail companies (Hou, 2012; Davenport, 2006) and banks (Olszak & Ziemba, 2007) are just some examples of BI&A's adopters.

One of the promises of BI&A is better and faster decision making, attained through higher quality of information and better insights into threats and opportunities (Hannula & Pirttimäki, 2003). Except from that, higher flexibility of analysis and usability of information is another possible result (Pirttimäki, Lönnqvist, & Karjaluoto, 2006). Finally, cost reductions and time savings can also be achieved (Hannula & Pirttimäki, 2003). Therefore, BI&A today is present in almost every company/organisation, something that is also supported by Chaudhuri et al. (2011, p.91) who state that "Today, it is difficult to find a successful enterprise that has not leveraged BI&A technology for their business".

However, the above mentioned promises of BI&A are not always fulfilled, as a result of IS/IT projects' failure (Wateridge, 1998). One reason of this failure is that despite the fact that companies/organisations keep investing on BI&A (Pirttimäki et al., 2006), the users keep underusing the provided tools. According to Gartner (2011), less than 30% of the end-users of BI&A tools, were actually using the tools in 2011. In order for companies/organisations to overcome a failure scenario, senior executives have to communicate the adoption of an IT system with their employees, to be the leaders of this change, in order to convince them about its beneficial usage (Davenport, 2006). Apart from effective communication, training is being used by many companies/organisations as a way of getting end-users more familiar with the new system (Davenport, 2006; Gupta, Bostrom, & Huber, 2010).

Triggered from the above mentioned failures and in order to understand the factors that lead to an IS success, researchers came up with the result that end-user computing satisfaction (EUCS) is one of the most important ones (Bailey & Pearson, 1983; DeLone & McLean, 1992; Doll & Torkzadeh, 1988). Consecutively, EUCS is inevitably connected with information systems (IS) usage since without usage there is no satisfaction to measure. IS usage is defined as the extent to which users make use of a technology/information system, in order to complete their tasks (Goodhue & Thomson, 1995).

Unfortunately, even if high system usage and satisfaction are achieved there is always a chance for the IS/IT project to fail in a later phase (Bhattacherjee, 2001). This observation led Bhattacherjee (2001) as well as other researchers, such as Zmud (1982), to examine the so-called usage continuance intention (UCI). Its difference compared to EUCS is substantial, as UCI makes a distinction between the initial and the long-term acceptance (Bhattacherjee, 2001). Thus, even if users do accept an IS system in an early adoption phase, this does not stop them from a possible rejection in a later phase.

The above mentioned concepts of EUCS, training, system usage and UCI as well as the studies and surveys around BI&A serve as our motives and the main objects of this study, that are going to be investigated through this paper.

1.2 Problem Area

BI&A, as it has been previously said, can give a chance to companies/organisations to stand out of the crowd through better decision making. Companies/organisations can choose, according to their needs, between the three types of BI&A, namely descriptive, predictive and prescriptive, nonetheless, descriptive BI&A is the most commonly used one (Evans, 2012). According to Bertolucci (2013) 80% of the BI&A that is used today is descriptive. This is something which is completely reasonable if we take into consideration its valuable usage for a company/organisation (Evans, 2012). Therefore, we find urgent the need for this particular category of BI&A to be examined. Consequently, our aim in this paper is to address end-users' perceptions and attitudes towards descriptive BI&A. In order to do that, we will make use of the EUCS model (Doll & Torkzadeh, 1988). EUCS model has been cross validated and has been used for measuring EUCS for many information systems like ERP systems and Hospital Information Systems (HIS) (Somers, Nelson, & Karimi, 2003; Mitakos, Almaliotis, & Demerouti, 2011; Aggelidis & Chatzoglou, 2012; Weli, 2014). Hence, we believe that it is the most trustworthy one for conducting our research, even though it has been used only once in a BI&A context by Hou (2012).

Moving on to system usage, rejection that derives from low system usage of a computer-based application is many times being done by the end-user for a variety of reasons, like low perceived usefulness and satisfaction (Bhattacherjee, 2001). IS usage's importance is obvious since without usage, the system has failed to achieve its purpose. Consequently, the investment on such a system would not bring the expected benefits.

Concerning system usage in the BI&A context, a survey which was conducted in 2013, revealed that the usage of BI&A software among employees, despite its top-level priority (Gartner, 2013), is at 22% (Cindi Howson, 2014). This is an evidence that either BI&A's potential benefits are still not obvious to its users or users' EUCS is low. Even though system usage has already been investigated by many researchers during the last decades, such as Straub, Limayem and Karahanna-Evaristo (1995) who examined the ways of measuring system usage, Bajaj and Nidumolu (1998) who examined the relationship between system usage and past usage, and Compeau, Higgins and Huff (1999) who proved that system usage improves the EUCS of computer-based IS, the relationship between EUCS and system usage is not broadly tested in the BI&A context. Only Hou (2012), according to our knowledge, confirmed this relationship in a research which was conducted in Taiwan. Hou (2012) revealed that higher system usage leads to higher EUCS. Since this study was only targeting the electronics industry our tension is to test the same using another sample.

Despite the efforts that are being done by the companies/organisations for the BI&A adoption, such as training and effective communication which have been mentioned previously, a Gartner's survey (2011) revealed that one of the reasons why BI&A users do not use the system is that they find it difficult to use. In the IS literature, education and training services have been proven to improve the EUCS of computer-based IS (Nelson & Cheney, 1987), Nickerson (1999) pinpointed lack of training as one of the reasons why users may not use a system, while Aggelidis and Chatzoglou (2012) confirmed a positive relationship between training and EUCS. Yet, to the best of our knowledge this relationship has not been tested in a BI&A context.

Finally, regarding UCI and the fact that users may reject a computer-based application in a latter phase, the BI&A systems could not be an exception. We have found that the research which has been conducted investigating the relationship between EUCS and UCI is limited. Chang, Chang, Wu, and Huang (2015) and Chou and Chen (2009) were some of the researchers who investigated in different contexts, long-term care (LTC) IS and ERP systems respectively. Inevitably, there is a need to better understand the factors that increase EUCS so as to mitigate the chance of rejecting the BI&A system, and predict, explain and increase its UCI. Consequently, the last relationship that will be examined will be the one between EUCS and UCI in a descriptive BI&A context.

The mentioned facts in the problem area served us as the main motivations towards examining the end-users' perception of EUCS, system usage, training and UCI and the relationships that exist among them in the context of BI, and specifically descriptive BI&A. To the best of our knowledge, this research has not been conducted before.

1.3 Research questions

The questions that are presented below are the main tasks that will be covered in this study. The research questions are:

1. How does training influence the system usage of descriptive BI&A systems?

2. How does training and system usage influence end-user's satisfaction regarding EUCS of descriptive BI&A systems?

3. How does EUCS influence the UCI of descriptive BI&A systems?

1.4 Purpose

The purpose of the study is to examine the effect of EUCS within descriptive BI&A context and the relationship between EUCS, system usage, training and UCI. In order to achieve this purpose, we are going to measure EUCS and test the relationships/hypotheses between hypothetical factors by using an extended model based on the EUCS model by Doll and Torkzadeh (1988).

By conducting this study, our aim is to provide valuable information to companies and organisations which have adopted or which are thinking about adopting a BI&A tool. These companies/organisations gain insights in order to make the adoption successful as they get to know how users perceive training and system usage. What is more, they get to understand the specific aspects of BI&A tools that lead to higher EUCS, something that is also a valuable knowledge for BI&A vendors. All these eventually make them achieve higher UCI of the BI&A system.

As our problem is within the IS field, we intend to contribute to it by generating a valuable extension of EUCS model that could be implemented in other contexts of computer-based applications as well.

1.5 Delimitation

One delimitation of this study is that it examines only the perceptions of end-users, consequently it is limited to individuals' perspective. Apart from that, it is investigating only the descriptive BI&A, within the context of BI&A, therefore, it does not provide insights about the area of BI in general, even though the results could be applicable to other BI&A categories, namely prescriptive and/or predictive.

Since its focus is limited on the end-users of descriptive BI&A, such as people who work in departments, such as the supply chain, the sales or the marketing (Davenport, 2006), technical issues about the system which is used in each company, e.g. architecture of the system, will not be taken into consideration. This is also the reason why we did not choose to focus on a specific BI&A vendor.

Another delimitation that we face in this study is that it is examining only two factors that may affect EUCS, training and system usage. There are several different factors that have been proposed and examined as extended EUCS models, such as system speed and system reliability by Ilias, Razak, Rahman and Yasoa (2009). However, our study is not focused on one vendor. Inevitably, different BI&A systems may have different speed and reliability, offering limitations to ensure the model's robustness. Chou and Chen (2009) have also tested the effect of computer anxiety and general computer self-efficacy towards users' satisfaction something which we did not choose to examine as we believe that it is leaning more towards users' psychology.

2 Frame of Reference

2.1 Business Intelligence & Analytics

BI is a field which has been through transformations throughout the years (Watson, 2009) and it is argued by many to be one of the most valuable tools for companies and organisations nowadays (Chaudhuri et al., 2011; Gartner, 2013). Starting from the late 1960s, the DSSs became popular and were adopted by many organisations, especially after the development of the DSSs frameworks by Sprague and Watson (1975) and Sprague Jr and Carlson (1982). As years went by and technological advances were made, DSSs were continuing to be developed and it was in 1989 when Dresner first mentioned BI (Watson, 2009). Today a simple definition of what a BI system does is the following:

"BI systems combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers." (Negash, 2004, p.178)

In Figure 2.1 one can see the two crucial activities that BI encompasses which are "getting data in and getting data out" (Watson & Wixom, 2007, p.96).

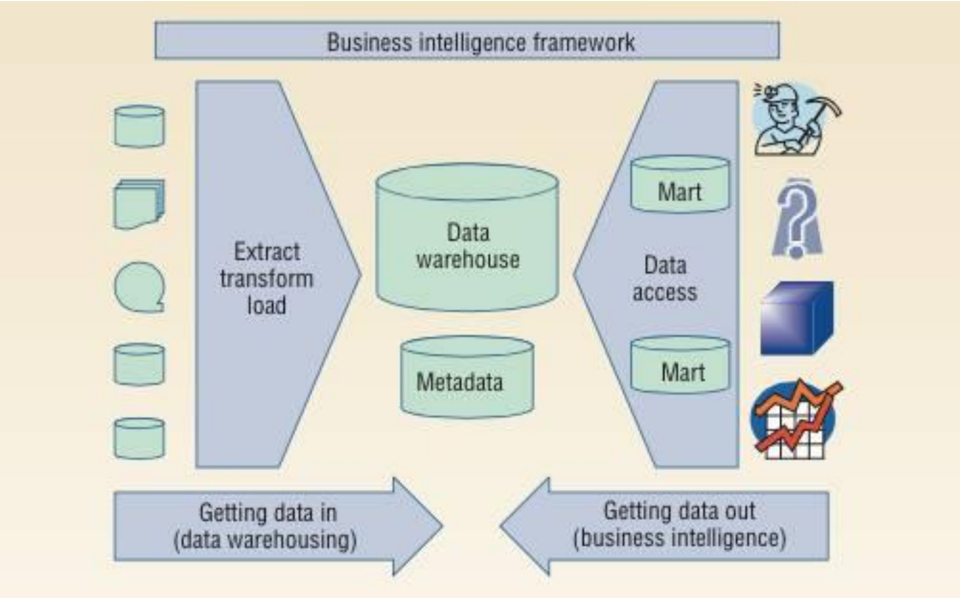


Figure 2.1 Business intelligence framework (Watson & Wixom, 2007)

ETL tools are used for preparing data before being added in the data warehouse (Chaudhuri et al., 2011). This preparation involves quality, validity and consistency checks (Chaudhuri et al., 2011). Once the data is inside the data warehouse servers, and before data is used in a BI tool, in order to get out to the end-user, data is entering the OLAP server in order actions like filtering and aggregations of data to be enabled (Chaudhuri et al., 2011). Finally, data is presented as an output though applications such as spreadsheets and dashboards (Chaudhuri et al., 2011). Of course, nowadays that the World Wide Web (WWW) has provided us with an enormous amount of unstructured data, new technologies like Hadoop and MapReduce are being used as well (Holsapple, Lee-Post, & Pakath, 2014).

BA was introduced as a term in the late 2000s' by Davenport (2006). In order to have a more clear view of the intelligence of BI&A, we will use Figure 2.2.

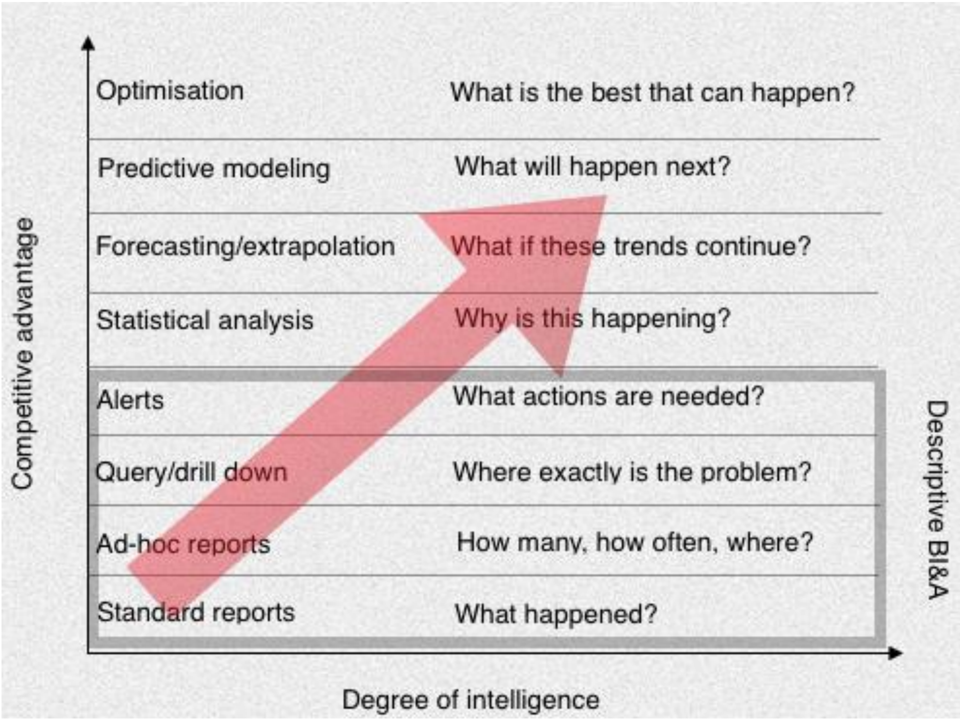


Figure 2.2 BI and BA (Sas, as cited in Davenport, 2006)

Figure 2.2 helps one to understand the degree of intelligence and competitive advantage that one can achieve through the use of BI&A tools. With the use of this figure one can see that the higher the intelligence, the bigger is the competitive advantage. The standard and ad-hoc reports, as well as the queries and the alerts are included in what is now called descriptive analytics (Evans, 2012). This is the most commonly used kind of analytics because it helps companies answer basic, yet important questions, like the amount of sales for a year and the revenues (Evans, 2012). Statistical analysis, forecasting and predictive modelling is the predictive analytics (Evans, 2012). Predictive analytics are used for predicting the future (Evans, 2012). Consequently, a company's/organisation's department such as marketing can predict future trends in the market. Finally, optimization, combined with statistical analysis, represents prescriptive analytics, which try to give an answer concerning the best solution that can be made under certain circumstances (Evans, 2012).

Figure 2.2 can also help us understand the connection between BI and BA. BI involves the technology which has already been mentioned, like OLAP and ETL and presents data through reports so we could claim that its output is the so-called descriptive analytics. On the other hand, BA involves more 'intelligent' techniques like statistical analysis and data mining (Chen et al., 2012). Consequently, we could say that BA is simply a more intelligent form of BI that is why we chose to use the BI&A term.

Looking through the history of BI&A Chen et al. (2012) divided its evolution into three periods. The first one which is called BI&A 1.0 is mainly based on databases including structured data (Chen et al., 2012). Capabilities like reporting, ad-hoc queries, predictive modelling and OLAP are considered to belong to BI&A period (Chen et al., 2012). After the irruption and proliferation of the Internet, BI&A 2.0 bloomed (Chen et al., 2012). It was the period when unstructured data was introduced and researchers started talking about web and text analytics (Chen et al., 2012). Finally, BI&A 3.0 emerged with the increase in the use of mobile phones and tablets, especially after the launch of iPhone in the market in 2007 (Chen et al., 2012). This BI&A evolution brought changes not only to the market, for example through increased sales (Chau & Xu, 2012) and fraud detection (Abbasi, Albrecht, Vance, & Hansen, 2012), but also to the education system and the academia (Chen et al., 2012). Publications about BI&A increased and universities started offering bachelor and master degrees in BI&A (Chen et al., 2012).

Even though there is a long lasting debate between BI and BA, with researchers like Davenport & Harris (2007) arguing that BA is a subset of BI and others like Chen et al. (2012) who believe that the two terms are unified, we support the second opinion.

2.2 Theoretical background

User satisfaction has been investigated since end-user computing (EUC) was established as a term (Cheney, Mann, & Amoroso, 1986). EUC defines the changing role of users who used to cooperate with programmers in order to get information from a computer system, to their evolution as end-users who directly interacted with the computer system in order to enter information and prepare output reports (Davis & Olson, 1984). As stated by Simmers and Andandarajan (2001), user satisfaction definition has evolved as changes in the IS environment have been done. Yet, according to Doll and Torkzadeh, user satisfaction is "an affective attitude towards a specific computer application by someone who interacts with the application directly" (1988, p. 261).

Since user satisfaction was defined as a major issue within the IS community for computer-based applications, several studies have been done to address the factors of IS success, such as user acceptance and satisfaction (e.g. Davis, 1985; Cheney et al., 1986; DeLone & McLean, 1992; McKeen & Guimaraes, 1997; Nickerson, 1999). Different models have been created (e.g. Ives, Olson, & Baroudi, 1983; Bailey & Pearson, 1983; Igbaria, & Tan, 1997), with the most significant ones to be Technology Acceptance Model (TAM) by Davis (1985), DeLone & McLean (D&M) IS success model by DeLone and McLean (1992), and EUCS model by Doll and Torkzadeh (1988).

The TAM model created by Davis (1985) is based on Theory of Reasoned Action (TRA) which addresses human behavioural intention but TAM is formulated so as to address a technological-oriented way of user acceptance of the end-user IS computing (Davis, Bagozzi, & Warshaw, 1989). Therefore, users' technology acceptance is explained by behavioural intention, which is affected by perceived usefulness and perceived ease of use (Davis & Venkatesh, 1996). However, perceived usefulness and perceived ease of use may offer limitations to reflect on a variety of subject domains, as the external factors that are used in TAM model cannot be interpreted (Davis, 1985; 1989). Hence, TAM model needs to be extended and elaborated in order to address different areas and technology subjects (Chuttur, 2009), therefore, external factors could be chosen to reflect on the contextual settings and subjects of interest. In the aspect of EUCS, ease of use is also one of the components that EUCS model measures which, in jointly to the other components, addresses a more comprehensive aspect of user satisfaction, rather than user acceptance.

Another well-known model is D&M IS success model which is used for measuring the successfulness of a computer-based IS (DeLone & McLean, 1992). The model is classified into six categories of independent and dependent success variables: system quality; information quality; use; user satisfaction; individual impact; and organisational impact (DeLone & McLean, 1992). About 10 years later, DeLone and McLean (2003) revised the D&M IS success model to an updated version which also consists of six IS success categories: system quality, information quality; service quality; usage (intention to use and use); user satisfaction; and net benefits. However, the latest model is more e-commerce oriented (DeLone & McLean, 2003). Despite that, Doll, Deng, Raghunathan, Torkzadeh, and Xia (2004) positively address the fact that the updated model still considers user satisfaction as an important factor of IS success, as DeLone and McLean (2003) assess end-user satisfaction in relation to usage and organisational performance. In addition, in the updated model, user satisfaction success category is being affected by use success sub-category and is affecting the intention to use success sub-category (DeLone & McLean, 2003), something that we aim to test in this study by system usage, EUCS and UCI.

Regarding user satisfaction instruments, the initial instrument for measuring user satisfaction that had been characterized as reliable (Omar & Lascu, 1993), was computer user satisfaction (CUS) instrument by Bailey and Pearson (1983). The CUS instrument consisted of 39 items (Bailey & Pearson, 1983). Based on CUS instrument, Ives et al. (1983) developed user information satisfaction (UIS) instrument, and then, Baroudi and Orlikowski (1988) transformed it to its short-form that included 13 items for measuring user satisfaction. UIS refers to the degree that users' perceptions evaluate that the IS in use meets their information requirements (Ives et al., 1983). Even though these instruments measure general UIS -satisfaction of the provided and in use information-, they are the basis of the specific-computer-based application UIS instrument, namely the 12-item EUCS model by Doll and Torkzadeh (1988).

2.2.1 End-User Computing Satisfaction (EUCS) model

In 1988, Doll and Torkzadeh created the EUCS model so as to measure the factors that affect users' satisfaction of computer-based IS, where users, as stated by Cotterman and Kumar (1989), are the end-users who directly interact by using the computer with a specific IS. Based on previous studies (Ives et al., 1983), they wanted to develop a standard measurement of EUCS (Doll & Torkzadeh, 1988). The outcome was a multifaceted 12-item instrument which requires the end-users' subjective perceptions of the five end-user satisfaction components, namely content; accuracy; format; ease of use; and timeliness, so as to measure EUCS (Doll & Torkzadeh, 1988). The EUCS and its components are represented in figure 2.3. In addition, Table 2.1 summarizes the definitions of EUCS model components.

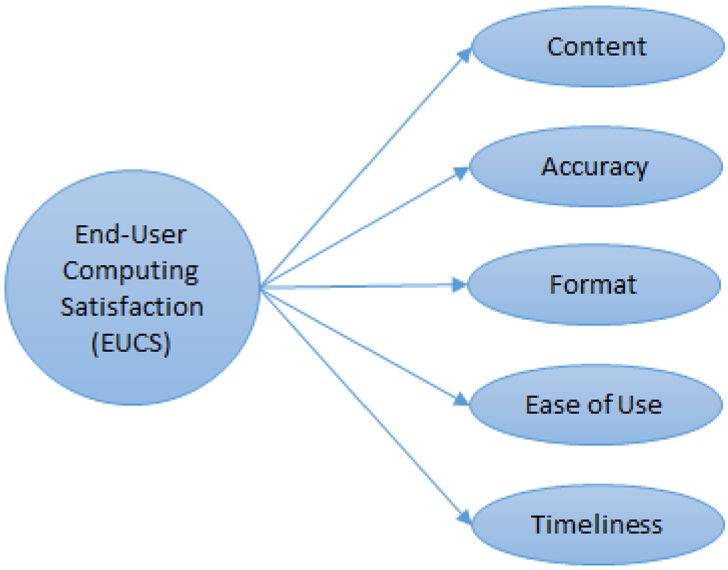


Figure 2.3 End-user computing satisfaction model by Doll and Torkzadeh (1988)

Table 2.1 Definitions of EUCS model (Bailey & Pearson, 1983, p.541)

Factor	Definition
Content	"The comprehensiveness of the information content"
Accuracy	"The correctness of the output information"
Format	"The material design of the layout and display of the output contents"
Ease of use	"The ease or difficulty with which the user may act to utilize the capability of the computer system"
Timeliness	"The availability of the output information at a time suitable for its use"

The model was defined as reliable and valid across a variety of IS applications (Doll & Torkzadeh, 1988). Consequently, as an empirical tested model, EUCS model is accepted as a reliable model able to determine the IS' success regarding end-users' satisfaction. Several studies have been done that measure EUCS of different computer-based systems, such as ERP, MIS, CAS, HIS and BI&A (Somers, et al., 2003; Mitakos, et al., 2011; Weli, 2014; Deng, Doll, Al-Gahtani, Larsen, & Pearson, 2008; Ilias, et al., 2009; Aggelidis & Chatzoglou, 2012; Hou, 2012). Many of these studies have redefined or extended the EUCS model so as to serve their needs and new emerging technologies aspects.

Despite its reliability, EUCS model had to overcome the IS community debate of cultural differences that may affect the model, since in IS research, questions may be raised about the results' validity of a model because of the different IS application in question or the cultural differences (Mullen, 1995; Myers & Tan, 2003). Consequently, apart from the obvious reasons of testing the validity and reliability of EUCS model, studies towards EUCS model are also checking the validity of the model towards different cultural and linguistic settings (e.g. McHaney, Hightower & Pearson, 2002; Heilman & Brusa, 2009; Mohamed, Hussin, & Hussein, 2009; Aggelidis & Chatzoglou, 2012). A significant study by Deng et al. (2008) tests the validity of EUCS instrument in MIS context across different national cultures. The sample of their study consists of five different nations/world regions of US, Western Europe, Saudi Arabia, India and Taiwan (Deng et al., 2008). Their results show that no difference occurs to the regions tested, revealing that EUCS is still robust across different cultures and that cultural differences are not of the significant factors affecting EUCS (Deng et al., 2008). This fact assures that even if IT applications do have different implementation and usage in different world region, EUCS is still valid.

As previously mentioned, EUCS model has been used in evaluating user satisfaction of various systems and in different ways so as to interpret different technology aspects. For example, we have identified three conducted studies in ERP context that validate the model in different manners. Somers et al. (2003) conduct their study, working on a confirmatory factor analysis framework of EUCS, in order to cross-validate and retest it. Additionally, Mitakos et al. (2011) redesign the model in order to address human factors, perceived usefulness and self-efficacy that may influence ERP user's satisfaction. Finally, Weli (2014) tests the manager's satisfaction of ERP systems and whether manager's satisfaction influence manager performance.

Table 2.2 is used to summarise a variety of conducted studies of EUCS model in IS research. The fact that some of the studies involve only student users may limit the reflection of real-world situations (Kim & McHaney, 2000; Xiao & Dasgupta, 2002; Wang, Xi, & Huang, 2007). In addition, results from a single-case company cannot be generalised (Bhattacherjee, 2012).

Table 2.2 Overview of EUCS research in IS

Author	IS application	Model & extra components	Sample size	Main findings
Kim & McHaney, (2000)	Computer-Aided Software Engineering (CASE) tools	none	190 student end-users	They confirmed that EUCS is valid in CASE tool context
McHaney, Hightower, & Pearson, (2002)	Management IS (MIS)	none	342 end-users in 25 companies in Taiwan	They confirmed the validity of EUCS in Taiwan

Xiao & Dasgupta, (2002)	Web-based IS	11-item EUCS (dropped 1 question from content)	340 student end-users of 3 internet portals in US	They confirmed that the instrument provides a valid measure of user satisfaction
Somers, Nelson, and Karimi (2003)	ERP systems	none	407 end-users in 214 companies	The factor analysis has cross-validate the instrument
Pikkarainen, Pikkarainen, Karjaluoto, & Pahnila, (2006)	Internet banking	3-component EUCS (content, ease of use, accuracy)	268 end-users in Finland	They argued that only content, ease of use and accuracy are valid in measuring EUCS of online banking
Wang, Xi, & Huang (2007)	Group DSS (GDSS)	none	156 student end-users in China	The reliability and the validity are validated
Azadeh, Sangari, & Songhori, (2009)	IS: Administrative Automation, Pardaaz and Intranet	none	51 end-users of 8 offices in an Iranian power holding company	The end-users where classified into experts & no-experts. The validity of the questionnaire is confirmed.
Ilias, Razak, Rahman, & Yasoa, (2009)	Computerised Accounting System (CAS)	satisfaction with system speed & system reliability	90 end-users in finance department from 62 Responsibility Centres in Malaysia	They confirmed that users are highly satisfied with the system and that the most significant factors are ease of use, content and accuracy.
Mohamed, Hussin, & Hussein, (2009)	Electronic government systems	none	130 end-users in Malaysia	They confirmed that the EUCS model is valid and its measures are reliable
Mitakos, Almaliotis, & Demerouti, (2011)	ERP systems	perceived usefulness and self-efficacy	250 end-users in 4 Greek companies	The study proved a positive relationship between the extra constructs and EUCS
Marakarkandy & Yajnik, (2013)	Internet banking	none	387 end-users in India	They confirmed the validity of the model and the most important factors are format and timeliness
Weli, (2014)	ERP systems	managerial performance	71 managerial end-users	Confirmation that EUCS model is valid for measuring managers' satisfaction and that EUCS increase the managerial performance

In the literature review, we have seen studies that have shorten or extended the EUCS model. As we have argued, we aim to use an extended version of the model. The two studies illustrated below are the ones that influenced our decision for the extra components. In addition, the second one is in the context of BI&A.

Aggelidis and Chatzoglou (2012) test the EUCS in Hospital Information System (HIS) and have expanded the components of EUCS with the system processing speed; user interface; user documentation; user training; and user support in case of insourcing or outsourcing. The research is conducted on 283 users of HIS in a Greek translation of EUCS survey (Aggelidis & Chatzoglou, 2012). The enhanced version of EUCS model turns out to be valid and enable to enhance its generalisability and robustness as a valid measurement of computing satisfaction (Aggelidis & Chatzoglou, 2012).

In the context of BI&A, Hou (2012) creates a framework consisted of EUCS components to identify the relationship of EUCS, system usage and individual performance. The system under investigation is BI&A in Taiwanese electronics industry (Hou, 2012). The results indicate that EUCS positively affects BI&A system usage and individual performance and that BI&A system usage positively affects individual performance (Hou, 2012). Furthermore, a positive relationship exists between EUCS and BI&A system usage (Hou, 2012). The study by Hou (2012) addresses our tension to use system usage as a component affecting EUCS in our study. Thus, there is a research that addresses EUCS in the BI&A context that is limited in a specific industry and country. Further research to test the applicability of the results is needed so as generalisability to be implied.

The Hou's study (2012) is the only, to the best of our knowledge, study that has been done in the context of BI&A. Its above mentioned limitations reduce its generalisability. Also, the training factor has never been tested in the context of BI&A. Our study is done so as to fill this gap, as it is aiming in the descriptive BI&A context and the relationships between EUCS, training, system usage and UCI. The next subsections are devoted in the description of the importance of the other components, namely system usage, training and UCI.

2.2.2 System Usage

System usage is perceived by many researchers as one of the factors that affect an information system's success (Szajna, 1993). Lucas Jr (1978) was one of the first who pointed out the importance of measuring system usage as a system that is not used, is also not successful. Yet, despite the conducted studies, system usage is a term which has many different interpretations. According to Burton-Jones and Straub Jr (2006), it includes three constructs: 1) the system, 2) the user and 3) the performed task. In order to measure system usage, many different measurements have been used, such as duration and frequency of use, extend of use and voluntariness of use (Burton-Jones, 2015).

No matter what the difficulties of defining system usage and its measures are, many researchers have conducted studies in order to find out how system usage affects different factors of IS' success. Islam (2013) examined how an e-learning system's usage affects a student's academic performance, while Nwankpa confirmed in 2015 that an ERP system's usage has a positive association with an EPR system's benefit.

2.2.3 Training

Reasons, such as time-consuming, individual effort and no-expert or no system support are used by end-users who are not using or expand the capabilities of computer-based applications (Nickerson, 1999). This pinpoints the importance of training as part of an organisation's strategy (Miri, Mansor, Chasempour, & Anvari, 2014), especially in the case when a new system is adopted. Its vital role keeps being underlined in plenty of articles in Fortune magazine (Stern, 2011) and in Business Insider (Horowitz, 2010). Cermak and McGurk from McKinsey & Company presented in 2011 through a case study that after a training program a company generated returns more than four times the cost of the program.

The valuable role of training has also led many researchers study it. Gupta et al. (2010) conducted a literature review of the end-user training (EUT) methods which turned out to be divided into three broader categories: 1) Pre-training, 2) Training and learning process, and 3) Post-training. According to them, the training methods are decided upon the training goals which could be: 1) skill, 2) cognitive, 3) affective, and 4) meta-cognitive (Gupta et al., 2010). Torkzadeh and Van Dyke examined in 2002 the relationship between training and Internet self-efficacy, while Aggelidis and Chatzoglou (2012) confirmed a positive relationship between training and system quality.

2.2.4 Usage Continuance Intention (UCI)

UCI is a concept which has many different aspects. Researchers have connected it with IS implementation (Zmud, 1982), although in this paper our approach is closer related to Bhattacherjee's (2001) approach. What Bhattacherjee (2001) did was that he correlated UCI with an IS's post-adoption phase and connected it with Expectation-Confirmation Theory (ECT) (Oliver, 1980).

Apart from Bhattacherjee, many other researchers have also tried to explain UCI. Chang et al. (2015), examined the way that users' satisfaction and performance impact affect UCI, whereas Chou and Chen (2009) tested the effect of computer anxiety, satisfaction and general computer self-efficacy on UCI. Limayem and Cheung (2008) on the other hand differentiated from Bhattacherjee and examined UCI and IS continued use. Finally, Chiu and Wang (2008) examined different factors that affect UCI, such as attainment and utility value as well as effort and performance expectancy, in a Web-based learning context.

2.3 Research model and hypotheses

In order to answer our research questions, there is a need to propose a research model (Figure 2.4) with hypothetical factors and test it. Through this model we will be able to measure EUCS and test the posed hypotheses between the factors. Through the constructs of the model the EUCS will be measured while later comes the testing of the hypothesised causal relationships between the constructs.

Regarding EUCS, further studies revealed that training (Soliman, Mao, & Frolick, 2000) and system usage (Baroudi, Olson, & Ives, 1986) do affect the EUCS. On the other hand, system usage is found to be affected by training (Compeau et al., 1999) and EUCS (Hou, 2012). Finally, EUCS affects system usage (Hou, 2012) and UCI (Chang et al., 2015).

The factors and hypotheses of the proposed model are discussed in-depth below.

2.3.1 Training & End-User Computing Satisfaction (EUCS)

The relationship between training and satisfaction has been tested and confirmed as positive by Mykytyn (1988) within a DSS context. The same has been confirmed in an ERP context (Dezdar & Ainin, 2011; Al-Jabri, 2015). Aggelidis and Chatzoglou (2012) also prove that training is an important factor of a new proposed EUCS model. However, to the best of our knowledge, the relationship has never been tested in a BI context, that is why the following hypothesis is proposed:

H1: Training has a positive effect on End-User Computing Satisfaction (EUCS) of BI&A.

2.3.2 Training & System Usage

Compeau et al. (1999) have investigated the relationship between the training and the system usage and have found a positive relationship between the two constructs. Consequently, the higher the level of training, the higher the users' use the system. Similar are the results of the study that is conducted by Rouibah, Hamdy and Al-Enezi (2009) who confirmed a positive indirect relationship between training and system usage. Hence, the following hypothesis is proposed for being tested:

H2: Training has a positive effect on System Usage of BI&A.

2.3.3 End-User Computing Satisfaction (EUCS) & System Usage

Plenty of research studies have investigated the relationship between EUCS and system usage at an individual level. Hou (2012) has proved that higher level of EUCS leads to higher level of system usage and vice-versa, within a BI context in Taiwan. DeLone and McLean (2003) indicate that a rise in the level of user's satisfaction will lead to higher level of usage intention, something that will, consequently, positively affect the system usage. Rouibah et al., (2009) confirm a positive relationship among system usage and EUCS. Therefore, the following hypotheses are proposed in order to test if Hou's (2012) results are also valid outside of Asia:

H3: System Usage has a positive effect on End-User Computing Satisfaction (EUCS) of BI&A.

2.3.4 End-User Computing Satisfaction (EUCS) & Usage Continuance Intention (UCI)

Bhattacherjee (2001) has investigated the relationship between users' satisfaction and IS continuance intention and confirmed that the higher satisfaction leads to higher UCI. Chang et al. (2015) confirm this relationship in an LTC context. Furthermore, Chou and Chen (2009) do the same in an ERP context. Finally, Zhou (2011) confirms the relationship in a context of mobile payments.The purpose of the following hypothesis is to examine the same relationship in a BI context:

H4: End-User Computing Satisfaction (EUCS) has a positive effect on Usage Continuance Intention (UCI) of BI&A.

In order to summarize the above hypotheses, Figure 2.4 illustrates the proposed research model of the extended EUCS, including the hypothetical constructs and the hypotheses that are represented by arrows. The proposed research model assumes that the hypotheses in question are true in the context of descriptive BI&A and will be tested in this research's process. Table 2.3 summarizes the hypotheses between these constructs.

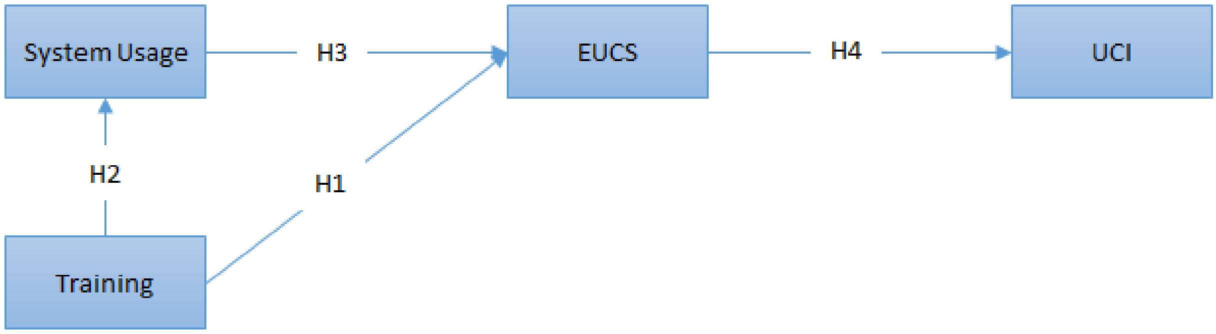


Figure 2.4 Research model and hypothetical factors

Table 2.3 Hypotheses within the proposed model

Path and code	Hypothesis
TR → EUCS	H1: Training increases the End-User Computing Satisfaction (EUCS) of BI&A
TR → SU	H2: Training increases the System Usage of BI&A.
SU → EUCS	H3: System Usage increases the End-User Computing Satisfaction (EUCS) of BI&A.
EUCS → UCI	H4: End-User Computing Satisfaction (EUCS) increases the Usage Continuance Intention (UCI) of BI&A.

3 Methodology

3.1 Research strategy

The first phase when conducting a research is the exploration (Bhattacherjee, 2012). In this phase, three iterative steps are included: 1) forming of your research questions, 2) conducting a literature review and 3) searching of theory that will support your research (Bhattacherjee, 2012). In order for us to define the research questions, which have already been formed and were presented above, we used the gap spotting technique (Alvesson & Sandberg, 2011). Consequently, after having decided about the domain of our interest (Bhattacherjee, 2012), which was BI&A, we conducted a literature review in order to get deeper knowledge about this field and identify some interesting and useful questions that have not been asked before. Once this was done, the next step was to find cross-validated and robust theory that will support our research. After repeating these steps many times, the first phase was completed.

The second phase of a research is the research design phase (Bhattacherjee, 2012). This is the phase where a plan of how exactly the research will be conducted is designed. A well-formed plan will lead us to answering our research questions. This phase is devided into three steps: 1) operationalization, 2) research method and 3) sampling strategy (Bhattacherjee, 2012). The first step concerns the formulation of the constructs that will be used for a research. Then comes the research method choice. Whether a researcher decides upon conducting a qualitative, quantitative, experimental or mixed method is something based on the topic of the studies and the type of data that one wishes to collect (Bhattacherjee, 2012; Recker 2013). To test our proposed model and answer the posed research questions, we chose a quantitative method, as it is the one appropriate for the usage of EUCS model. Specifically, we conducted a survey, as it is appropriate for studies that have individuals as target of investigation as well as for testing a model (Bhattacherjee, 2012; Recker 2013). Finally, the last step of this phase, the so-called sampling strategy, concerns choosing the appropriate population for conducting a research (Bhattacherjee, 2012).

After the previous preparation phases, the last one is the research execution phase (Bhattacherjee, 2012). This is the phase when the actual research is conducted, consequently it involves: 1) pilot testing, 2) data collection and 3) data analysis (Bhattacherjee, 2012). Pilot testing serves for testing your chosen measurement instruments (Bhattacherjee, 2012). Data collection involves the actual distribution of the survey and the collection of the results, while the data analysis part refers to the analysis and the interpretation of the given answers (Bhattacherjee, 2012). In our case, this involved the use of IBM SPSS and IBM AMOS software packages.

Since the main phases of the research have been described, we will now proceed with a further analysis of the above steps.

3.2 Data collection

3.2.1 Literature review

Conducting a thorough literature review is the first thing we had to do for this paper. Its importance has been presented by Hart (1998) who identified the reasons for conducting a graduate student thesis literature review: 1) the student gains a hollistic view of the subject, 2) it helps identifying the existing gap, 3) it is a proof of the student's hard work and dedication. Consequently, we searched through the existing literature in order to find information about BI&A studies and about the different models which are used for assessing EUCS and UCI.

For our literature review, we followed the proposal of Webster and Watson (2002) for conducting a structured literature review. Therefore, we started by searching for the major contributions in articles and databases like ACM Digital Library, Emerald and Science Direct. Once we had identified these papers, we went backwards by looking at their citations and then forward by using Web of Science.

3.2.2 Sampling process

Before sending out our survey, we had to conduct the sampling process (Figure 3.1).

Population:
The group you want to generalize to
(e.g., professional workers around the world)

Sampling Frame:
A list from where you can draw your sample
(e.g., employees at 1-2 local companies)

Sample:
The actual units selected for observation
(e.g., a random selection of employees at each firm)

Figure 3.1 Sampling process (Bhattacherjee, 2012)

First step in this process is defining our target population which will be the unit of analysis of this study (Bhattacherjee, 2012). Based on the fact that our research is focused on users of descriptive BI&A tools, our targeted population was employees who use such tools in order to conduct their work. Once the targeted population had been decided, the next step was the decision about the sampling strategy (Bhattacherjee, 2012).

The second step of the process is the sampling frame choice (Bhattacherjee, 2012). In this phase, researchers usually do make a list with their possible respondents (Bhattacherjee, 2012). The problem in our case was that we had no names of the employees. What we did was that we found companies from BI&A's vendors sites and made a list with these companies. In order our sample not be biased - and have only users of three BI&A tools - we also included some other companies that we knew. The companies were from Greece, Sweden and United Kingdom, in order for us not to have problems caused by the language barriers. What is more, the chosen companies were not operating in the same industry and were not of the same size, in order our results to be generalizable (Bhattacherjee, 2012).

Finally, the last thing that had to be done, was to make a decision about the sampling technique that we would follow. There are two types of techniques from which we had to choose: 1) propability sampling techniques and 2) non-propability sampling techniques (Bhattacherjee, 2012). Even though quantitative methods of data collection rely mostly on propability sampling techniques, and especially random sampling (Recker, 2013) for generalizability reasons (Bhatacherjee, 2012), we could not make use of this technique. Therefore, our choice was to use the convenience sampling technique (Bhattacherjee, 2012).

This kind of technique allows to the researchers to draw samples which are more accessible to them (Bhattacherjee, 2012), something which we also needed because of the time-limit. The sample units in this research were employees/end-users of BI&A tools in companies and organisations. Consequently, what we did was that we distributed the questionnaire to their managers, since they had the contact information, and they sent the questionnaire to the appropriate employees via email. By the end of the distribution, this number was 103 employees out of 16 companies.

3.3 Development of questionnaire

3.3.1 Design of questionnaire

When designing a questionnaire, especially one that is administered to end-users/individuals like we did, we have to have in mind that the respondent has to understand the purpose of the study in order to give valid answers. Consequently, we included an introduction in the beginning of our questionnaire informing the participants about our study and our intentions as well as about anonymity issues which will be further developed in another section.

For this study, the questionnaire was composed of two parts (see Appendix *I).* The first part includes demographic and general questions which are structured and unstructured. The results of personal information, containing questions, such as gender and work position, were not analysed in-depth, but were used for increasing the study's transparency. What is more, we wanted to see the distribution of men and women and the departments that mostly use BI&A tools. While general questions contain questions such as elapsed time since adoption of BI&A system and BI&A experience, duration of BI&A's usage and frequency of usage - which were the two indicators measuring system usage- were also added in this part. We decided to use them in the first part of the questionnaire so as to achieve better sequencing of questions as they are more general than the second part of the questionnaire. The second part of the questionnaire included the main questions of this research. We designed it using degree questions which could measure the different constructs and the relationships between them of our proposed model. In order to form the right questions for our survey, we searched in previous studies and used questions that have been used before for measuring the same construct, and are therefore validated.

In order to measure satisfaction, the EUCS model (Doll & Torkzadeh, 1988) was used. Its five components, namely content, accuracy, format, ease of use and timeliness, were measured through the use of items (four, two, two, two and two relatively). In order to rate the answers, Likert-scale, the most commonly used type of scale in social science research (Bhattacherjee, 2012) was used, namely a five-point Likert-type scale. The answers which were varying from 1='Strongly disagree' to 5='Strongly agree' were constructed, and respondents had to indicate their level of agreement or disagreement towards the posed questions.

Training was measured through the use of four items (TR1, TR2, TR3, TR4) and the five-point Likert scale which was mentioned above. These items have been used before by Rouibah et al. (2009) and measure training through measuring its sufficiency, course material, the clarity of the training's objectives and the role of the participant and the availability of after-training support.

Regarding UCI and its measurement (UCI1, UCI2, UCI3), Bhattacherjee's (2001) items were used. Through using these items, the participants could indicate if they intend to continue using the BI&A tool and the reason behind their intention - is it because they have no alternatives or is it their choice?-. Again, a five-point Likert-type scale. The answers from the five-point Likert-type scale were varying from 1='Strongly disagree' to 5='Strongly agree'.

Finally, as mentioned previously, the assessment of system usage was conducted through examining 1) the duration (SU1) and 2) the frequency of the BI&A's usage (SU2), something which has been done by Hou (2012). In order to rate these answers, two five-point scales were used ranging from 1='Less than 20' (minutes) to 5='More than 120' (minutes) for duration and from 1='About once a week' to 5='More than 4 times a day' for frequency.

The questions, which were rephrased in order to relate to the study's BI&A context, were formed based on our hypotheses and together with the information of constructs they are presented in Table 3.1.

Table 3.1 Hypothetical factors, definition of constructs and measurement items

Construct/ Hypothetical factor		Definition	Measurement Items	Source
EUCS	**Content**	The degree to which the content of the system is perceived as precise and sufficient.	**C1**: The BI&A system provides the precise information I need. **C2:** The BI&A's information content meets my needs. **C3:** The BI&A system provides reports that seem to be just about exactly what I need. **C4:** The BI&A system provides suffi-	Doll & Torkzadeh, 1988

		cient information.	
Accuracy	The degree to which the system is perceived as accurate.	**A1:** The BI&A system is accurate. **A2:** I am satisfied with the accuracy of the BI&A system.	Doll & Torkzadeh, 1988
Format	The degree to which the output of the system is perceived as useful and clear.	**F1:** The BI&A's output is presented in a useful format. **F2:** The information is clear.	Doll & Torkzadeh, 1988
Ease of use	The degree to which the system is perceived as user friendly-easy.	**E1:** The BI&A system is user-friendly. **E2:** The BI&A system is easy to use.	Doll & Torkzadeh, 1988
Timeliness	The degree to which the system provides up-to-date and on-time information.	**T1:** I get the information I need in time. **T2:** The BI&A system provides up-to-date information.	Doll & Torkzadeh, 1988
Training	The degree to which the training for the system is perceived as sufficient and effective.	**TR1:** The availability of training was sufficient. **TR2:** My role and the objectives before training were clear. **TR3:** The course material during training was adequate. **TR4:** The IT support after training was sufficient.	Rouibah et al., 2009
System Usage	The degree to which the users make use of the system.	**SU1:** How much time do you spend each week using the BI&A system **SU2:** At present how often do you use the BI&A system	Hou, 2012
UCI	The degree to which the users intend to keep using the system.	**UCI1:** I intend to continue using the BI&A system than discontinue its use. **UCI2:** My intentions are to continue using the BI&A system than use any alternative means. **UCI3:** Even if I could I would not like to discontinue my use of the BI&A system.	Bhattacherjee, 2001

3.3.2 Pilot testing

Pilot testing is an important part of the research (Bhattacherjee, 2012). It adds reliability and validity to the questionnaire and its constructs (Bhattacherjee, 2012), consequently we conducted one in order to identify possible problems and rectify them before sending the final questionnaire to the participants (Recker, 2013). For the purposes of the pilot-testing, we chose a small sample of our targeted population. Therefore, we distributed the questionnaire through email to 11 persons who have experience using a BI&A tool. Apart from answering the questionnaire, the participants gave us feedback such as suggestions which would help to increasing the quality of our questionnaire. All of the respondents made a comment about the suggested time needed for the completion of the questionnaire as the initial time was 15 minutes, something that after the suggestions changed to 10. Some other problems came up after the pilot testing involved:

- Redundancy of questions
- Length of introduction
- Unclear words because of the translation from English to Greek and Swedish
- Spelling mistakes

After the suggestions we tried to improve our questionnaire. Therefore, we used the help of a professional translator in order to use more clear words which would make the questions more comprehensible and we corrected the spelling mistakes. Unfortunately, the problem of redundancy could not be resolved because these were the exact same questions used in all the previous studies and we did not want to decrease the validity of our questionnaire. Finally, the length of the introduction was decreased. After having refined the questionnaire, its final version was sent to the targeted companies and organisations for distribution to their BI&A tool's end-users.

3.3.3 Administration of questionnaire

Questionnaire surveys are divided into three types: 1) self-administered mail surveys, 2) group administered questionnaire and 3) online/web surveys (Bhattacherjee, 2012). For the purposes of this study, we chose to conduct an online/web survey using Google forms. The survey's link was sent via email to the appropriate manager and then it was the manager's task to distribute the survey to the end-users of his/her company.

By using this type of questionnaire survey, we were benefited by its inexpensiveness as well as its time-saving and ease of distribution (Bhattacherjee, 2012; Recker 2013). What is more, the results were immediately available in an online database (Bhattacherjee, 2012; Recker, 2013). In order not to have multiple answers from the same respondent, we disabled this choice from the questionnaire. Furthermore, in order not to have the problem of unknown response rate (Bhattacherjee, 2012), every time that the questionnaires were distributed the manager was informing us about the number of the employees that would participate. Finally, in order to overcome the language barrier, the questionnaires were translated into Swedish and Greek.

3.4 Quantitative data analysis

Once all the data has been collected, the next step is the data analysis. In our case and since the collected data was mainly numerical values, our data analysis is quantitative. The types of data analysis from which we could choose are two: 1) descriptive and 2) inferential analysis (Bhattacherjee, 2012). Descriptive analysis is used for presenting/describing the constructs of the model and its associations as well as for aggregations, while inferential analysis is focused on theory testing, in this case the testing of the hypotheses (Bhattacherjee, 2012). Choosing which kind of analysis one will perform is a subject of one's posed questions. For our study, we conducted both types of analysis. In order to perform the data analysis Excel, SPSS and AMOS have been used.

Data preparation is the first stage of analysis, and involves: 1) data coding, 2) data entry, 3) manipulation of missing values and 4) data transformation (Bhattacherjee, 2012). Once the data was coded and entered into Excel, we had to take a decision about the missing values. The method that was followed was the so-called imputation process (Bhattacherjee, 2012). Consequently, even if a value was missing, SPSS was making an unbiased estimation of the value (Bhattacherjee, 2012). We decided to follow this method because we did not want to shrink our sample size. Data transformation was not performed since there were no reversed values.

For the first part of our questionnaire, the demographics part, descriptive analysis was mainly performed - except of the system usage questions-. We used this kind of analysis in order to be able to interpret data such as work position and use of BI&A tools and variations among male and female users. Moving on to the second part of our questionnaire -plus the system usage questions-, both descriptive and inferential analysis was conducted. Descriptive analysis, specifically univariate and bivariate analysis (Bhattacherjee, 2012), was conducted. Through univariate analysis we were able to check the frequency distribution, the mean and the standard deviation of each construct's item, as well as the overall mean of each construct (Bhattacherjee, 2012). On the other hand, by using bivariate analysis, we could check the interrelationships between the constructs, consequently we conducted a bivariate correlation statistical analysis (Bhattacherjee, 2012).

The final part of our data analysis was the inferential analysis. For this part Structural Equitation Modelling technique (SEM) was used. SEM, which is a mix of factorial and regression or path analysis (Hox & Bechger, 1998), helped us test our initial hypotheses. Once the hypotheses were tested, the statistical significance and the path coefficients among factors were calculated. Figure 3.2 illustrates the factors, the items of each factor and the hypothesis made in this study.

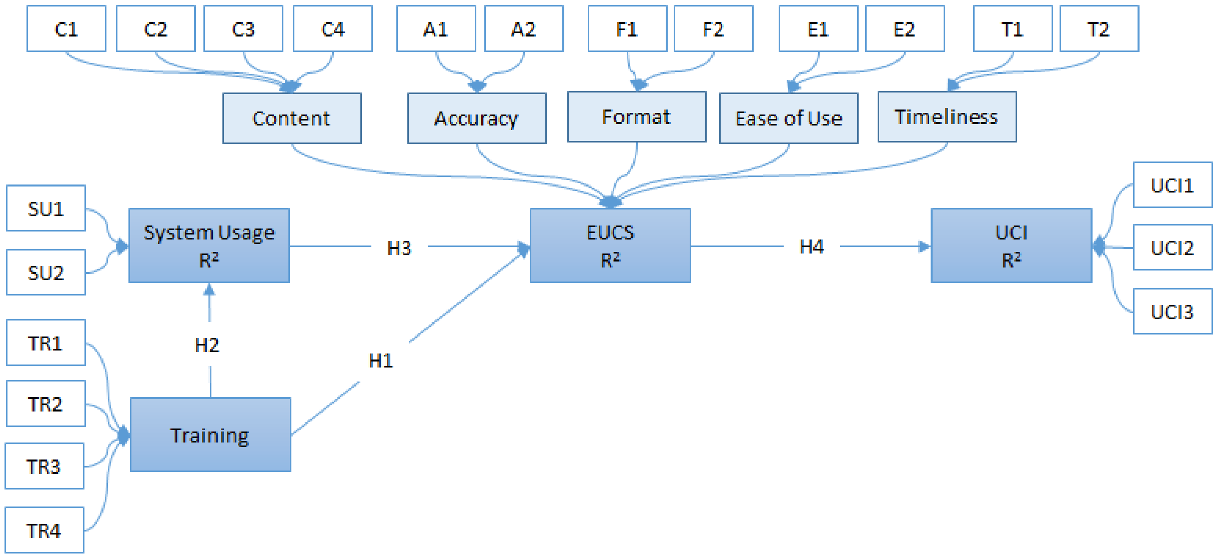


Figure 3.2 Explanation of hypothesis testing

3.5 Quality and ethics

Quality is a vital characteristic of a research therefore researchers strive to achieve high quality in their research papers. For the purposes of this study, quality was achieved through a combination of high reliability and validity (Bhattacherjee, 2012; Recker, 2013). Ethical principles that were followed will be also discussed below as ethics are highly related to the study's quality if we consider the fact that a data manipulation, for example, would damage both the validity and reliability of this paper.

3.5.1 Reliability

Reliability, according to Bhattacherjee (2012) and Recker (2013), is the degree to which construct's/model's measurement is consistent or dependable. This gives the chance to other researchers to repeat an already conducted research and find the same results. In order to measure the reliability, a researcher can choose among seven approaches: 1) interrater, 2) test-retest, 3) split-half, 4) internal consistency, 5) alternate forms, 6) composite and 7) unidimensional reliability (Bhattacherjee, 2012; Recker 2013). By using one of these approaches, a researcher can check its subjectivity interference in the study, especially when interviews are conducted (Recker, 2013).

Even though this study follows a quantitative approach, the test-retest approach would be ideal for checking its reliability. However, such an approach could not be implemented as it would need a lot of time to be completed. In this kind of reliability approach, questionnaires should have been sent twice to participants in order to make sure that there are no changes in their answers (Bhattacherjee, 2012). Therefore, in order to ensure the reliability of this study we chose to follow the internal consistency reliability approach. Consequently, Cronbach's Alpha statistical method was conducted (Bhattacherjee, 2012). The results of this approach will be presented more thoroughly in the next chapter.

3.5.2 Validity

Validity is divided into two different types: 1) validity of measurement procedures/construct validity and 2) validity of hypotheses testing procedures (Bhattacherjee, 2012). The concerns about construct validity are referring to whether the constructs are really representing what they ought to (Bhattacherjee, 2012; Recker, 2013). Construct validity can be assessed based on theoretical and/or empirical criteria (Bhattacherjee, 2012). Validity which is based on theoretical criteria is called translational validity, and is divided into two subgroups: 1) face and 2) content validity (Bhattacherjee, 2012). On the other hand, empirically assessed validity is divided into four subgroups: 1) convergent, 2) discriminant, 3) concurrent and 4) predictive validity (Bhattacherjee, 2012).

An issue about our constructs' validity could be that a questionnaire item is ambiguous and gives the impression to the respondents that it means something else than what it should (Recker, 2013). So as to overcome this, we conducted convergent and discriminant validity tests. Therefore, convergent validity was evaluated with the average variance extracted (AVE) (Hair, Anderson, Tatham, & Black, 1998). Additionally, for the discriminant validity, we adopted Fornell and Larcker's (1981) suggestion of comparing the square root of AVE for each construct with the correlations between the constructs in our proposed model. Finally, we conducted statistical correlations between items through factor analysis (Recker, 2013). Factor analysis uses the bivariate correlation patterns that exist in the construct in order to aggregate the large number of items into smaller groups of unobserved patterns, which are called factors (Bhattacherjee, 2012). The construct is characterized by high validity if after the analysis the factors that will be created are the ones that we were expecting to be created (with the right correlations existing).

Moving on to the measurement of validity of the hypotheses testing procedures, the available approaches are three: 1) internal (causality), 2) external (generalizability) and 3) statistical conclusion validity (Bhattacherjee, 2012). Internal validity refers and tests the causality between a change of a dependent variable and the reason that this change happened (Bhattacherjee, 2012). Even though surveys are characterized by low internal validity, we tried to surpass this disadvantage by employing the above mentioned construct validity. Consequently, we created a model with constructs and items that have been used and validated before in order to achieve the highest possible internal validity.

Considering the external validity of our study, we achieved it through distributing the questionnaires to different types of companies and organisations, which operate in totally different industries in different countries of Europe. Apart from that, the end-users who answered the survey were employees in different departments, such as sales and marketing.

Concluding this part of quality testing, we also want to talk about the questionnaire's quality assurance. Bhattacherjee's (2012) guidelines were followed, consequently our final questionnaire included clear and understandable questions which were neither ambiguous nor worded in a negative manner. Too general, too detailed and double barrelled questions were also avoided as well as words that might bias the answers (Bhattacherjee, 2012). Finally, the sequencing of the questions was logical and it was following the structure of the constructs (Bhattacherjee, 2012).

3.5.3 Ethics

Ethical issues may rise when conducting a research, so the research should be harmonised with the Ethical Principles of Scientific Research as stated by Bhattacherjee (2012) which are 1) volunteer participation and harmlessness, 2) anonymity and confidentiality, 3) disclosure and 4) analysis and reporting. In our study, we informed the participants about their volunteer participation in the introduction of the questionnaire and that they could withdraw it any time they wanted by leaving the page. In the questionnaire's introduction, we also informed them about their anonymity, as there would be no attempt by us to associate the respondents with the responses. In addition, we disclosed our subject of study to the participants in the questionnaire's introduction so as them to be aware of our aims and the reasons why we want them to participate. An example of the introduction of the questionnaire that the ethical principles are included can be found in Appendix I. Finally, as we were aware of the fact that we may face unexpected or negative findings that do not fit our hypothesis, we intended not to carve the data in order to prove our hypothesis but disclosure our findings anyhow.

4 Empirical results and analysis

This chapter is dedicated to presenting the answers from the distributed questionnaires. As we have previously discussed, the participants were end-users of descriptive BI&A tools. From the distributed questionnaires (190), 103 were valid, consequently the response rate of this empirical study was 54.2 %.

4.1 Demographics-General questions

This section presents background information of the questionnaire's participants. Therefore, gender, department, work position, experience with the BI&A tool and the elapsed time since the adoption of the tool will be analysed. A summary of the results can be found in Appendix II.

4.1.1 Profile of the respondents

Regarding the gender of the respondents, as one can see in the Appendix II, the number of male participants were 55 a number which represents the 53.4% of the total. In comparison to that, the female users were 48 (46.6%), consequently, the proportion between men and women is almost equal. Our next question in the questionnaire concerned the department and the work position of the participants. For the department question, the participants could write the answer on their own. Consequently, the answers were many, such as credit control and supply chain, nevertheless most of the participants (19.4%) were working in the sales departments in their companies. Regarding the work position, we divided the answers into three groups (non-management/professional staff, middle-level management and top-level management/ executives), something which one can also see in Appendix II. The proportions of the work position are 55.3%, 36.9% and 7.8% respectively. Concerning the users' experience with the descriptive BI&A tools, the possible answers were three (less than one year, 1-4 and over five years). According to the respondents, 34% of them were working with such a tool for less than a year, 52.4% had 1-4 years of experience and 13.6% had more than five years of experience. Finally, the last question that respondents had to answer was regarding the elapsed time since the adoption of the BI&A tool. In this question we classified the answers to five subgroups (less than one year, 1-3, 3-5, 5-10 and over ten years) and the results were 8.7%, 51.5%, 31%, 6.8% and 2% respectively, yet the results are probably not that trustworthy because we had employees of the same company giving different answers.

4.2 Analysis of the proposed model

4.2.1 Measurement assessment analysis

A step prior to the analysis of our data in terms of the proposed model is testing our model's reliability and validity as it has already been mentioned in Chapter 3. In order to do that, we assessed the model's internal consistency as well as its construct validity.

Our first step was to conduct a Confirmatory Factor Analysis (CFA) (Jöreskog, 1967). In our study, what we expected to get through this analysis was a loading of eight factors, namely content, accuracy, ease of use, format, timeliness, training, system usage and UCI. In Figure 4.1 we see the results of this analysis.

	Component							
	1	2	3	4	5	6	7	8
C2	.868							
C3	.849							
C4	.831							
C1	.810							
TR2		.874						
TR1		.842						
TR3		.830						
TR4		.708						
UCI2			.873					
UCI1			.831					
UCI3			.816					
SU1				.969				
SU2				.962				
E1					.937			
E2					.922			
T2						.859		
T1						.851		
A2							.870	
A1							.851	
F1								.874
F2								.770

Figure 4.1 Results of factor analysis

Regarding internal consistency, Cronbach's alpha measurement was applied. Generally, the higher the Cronbach's alpha value, the higher is the internal correlation in the items of a construct. However, our goal was to achieve a value higher than 0.70 as it is proposed by Nunally (1978). Consequently, the Cronbach's alpha values of all the constructs in our model (content, accuracy, format, ease of use, timeliness, training, system usage and UCI) were measured and are presented in Table 4.1. All constructs' values are above the 0.70 threshold with numbers ranging from 0.855 to 0.96. Therefore, we are confident that our study has a satisfactory level of measurement reliability.

In order to measure our constructs' validity, we tested their convergent validity by measuring the Average Variance Extracted (AVE) (Fornell & Larckel, 1981). As we can see in Table 4.1, all of the constructs' AVE values are above 0.50 as it is suggested by Hair et al. (1998).

Specifically, the scores range from 0.643 to 0.924, indicating that our model's convergent validity is high.

Table 4.1 Reliability and validity testing

Constructs	Items	Factor loadings	Cronbach's alpha	AVE
Content			0.925	0.757
	C1	0.973		
	C2	0.980		
	C3	0.912		
	C4	0.889		
Accuracy			0.881	0.79
	A1	0.968		
	A2	0.921		
Format			0.856	0.765
	F1	0.915		
	F2	0.967		
Ease of use			0.916	0.853
	E1	0.993		
	E2	0.988		
Timeliness			0.855	0.75
	T1	0.922		
	T2	0.939		
Training			0.870	0.643
	TR1	0.862		
	TR2	0.802		
	TR3	0.807		
	TR4	0.645		

System Usage			0.96	0.924
	SU1	0.966		
	SU2	0.976		
UCI			0.863	0.683
	UCI1	0.887		
	UCI2	0.948		
	UCI3	0.860		

Apart from assessing the above mentioned convergent validity of our model, we also measured its discriminant validity. In order to do that, we followed Fornell and Larckel's (1981) suggestion of comparing the square root of AVE for each construct to the correlations between the constructs in our model. The results of this test are presented in Table 4.2 and, as one can see, the diagonal elements (square root of AVE) are greater than the non-diagonal elements something which shows high convergent validity (Fornell & Larckel, 1981).

Table 4.2 Validating the constructs' correlation of the model

	UCI	Training	System Usage	Accuracy	Format	Ease of Use	Timeliness	Content
UCI	(0,827)							
Training	0,201	(0,802)						
System Usage	0,156	0,013	(0,961)					
Accuracy	0,521	0,375	0,243	(0,889)				
Format	0,284	0,478	0,186	0,445	(0,874)			
Ease of Use	0,236	0,334	0,141	0,126	0,274	(0,924)		
Timeliness	0,327	0,291	0,147	0,274	0,515	0,146	(0,866)	
Content	0,474	0,422	0,107	0,478	0,521	0,232	0,558	(0,870)

4.2.2 Descriptive analysis

This section illustrates the data that were collected from our questionnaire. We discuss some main points which can be made regarding the proposed model's constructs and indicators. In

Appendix III, a Table shows the mean value and standard deviation of each item, while the overall mean value of each construct is also presented. As one can see, all the mean values are above 3.09, something which is a proof of generally positive users' perceptions and attitudes. In relation to the constructs of the model, the largest mean value belongs to content and timeliness (both of them scored 4.38) while the smallest one belongs to system usage (3.47). Below we will also present in graphs the percentage of the responses for each construct while one can find a summary of the descriptive statistics in Appendix IV.

EUCS

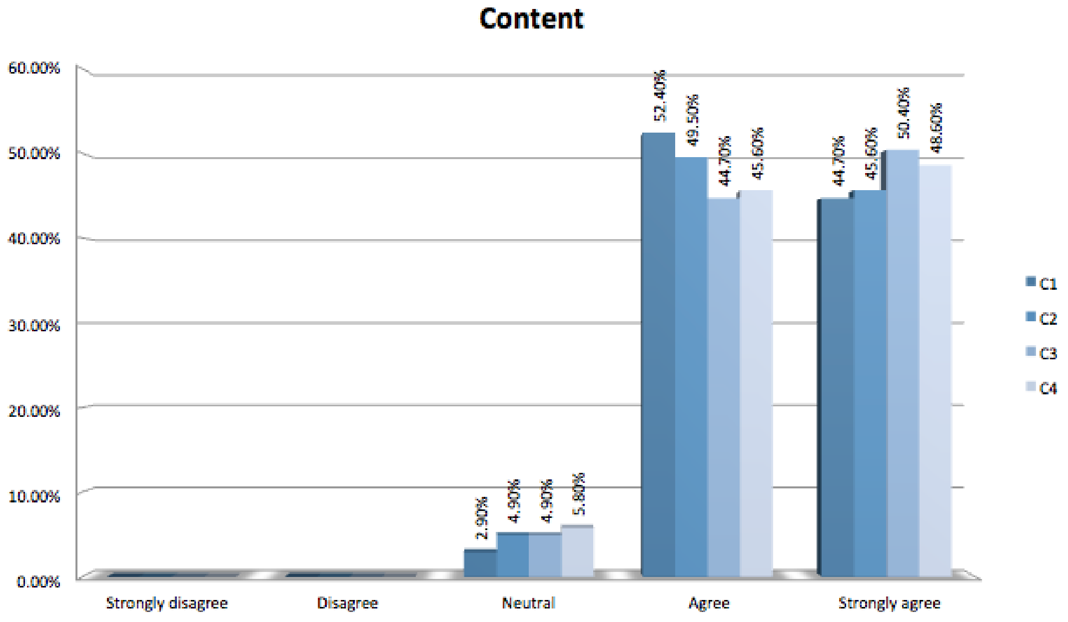


Figure 4.2 Responses (%) on content

Starting from content, its total mean value is 4.38, something which shows an indisputably positive users' perception. This is also supported by the respondents' answers which ranged from 'agree' to 'strongly agree' with just some few 'neutral' answers.

Moving on to the mean values of each item, the mean value of C3 is 4.46, the highest one among the contents' items. Specifically, 95.1% either agreed or strongly agreed that the reports that the BI&A system provided, were the precise reports they needed. Moving on to the other items, C1, C2 and C4 scored 4.24, 4.41 and 4.43 respectively. As one can see, all the mean values are high. 97.1% of the participants either agreed or strongly agreed that the information provided is precisely what the need (C1) and only 2.9% gave a 'neutral' answer. Furthermore, 95.1% 'agree' and 'strongly agree' that the content of the information meets their needs (C2), with 4.9% answering 'neutral'. Finally, 94.2% agreed or strongly agreed that the information provided is sufficient (C4) and 5.8% had 'neutral' opinion.

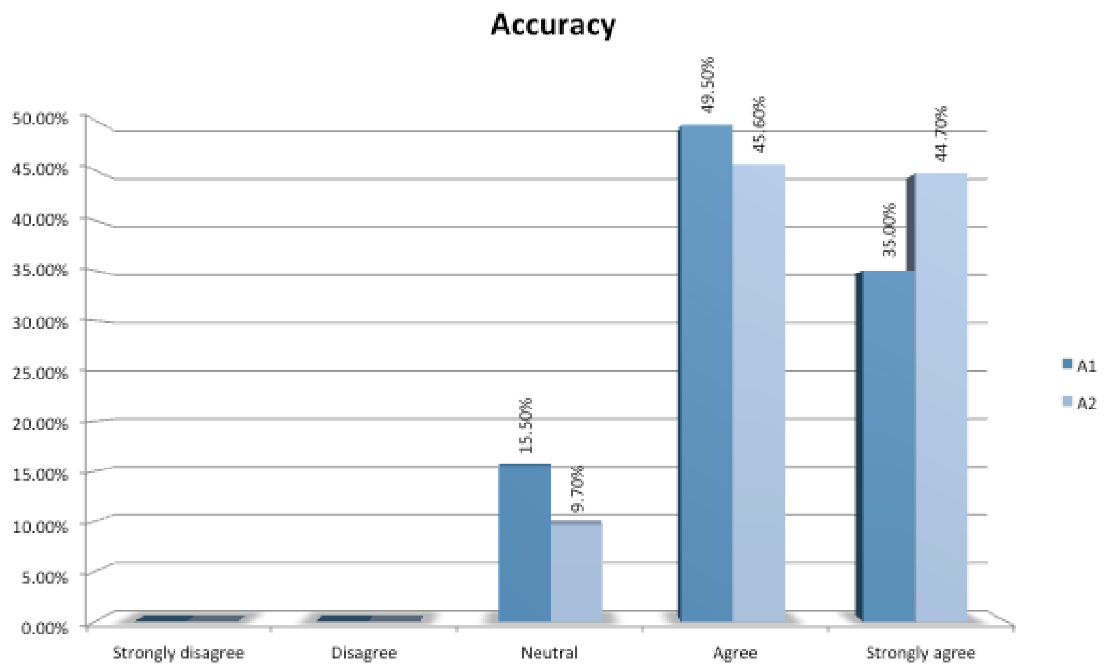


Figure 4.3 Responses (%) on accuracy

The overall mean value of accuracy, as one can also see in Appendix III, is 4.27, a number slightly lower than content. This result indicates that participants are generally quite satisfied with BI&A's systems accuracy. Within the construct, the items' mean values are 4.19 and 4.35 respectively. In addition, 84.5% of the respondents believe that descriptive BI&A systems are accurate (A1) with 15.5% having a 'neutral' opinion. On the other hand, 90.3% feel satisfied with the system's accuracy (A2) with 9.7% being 'neutral'.

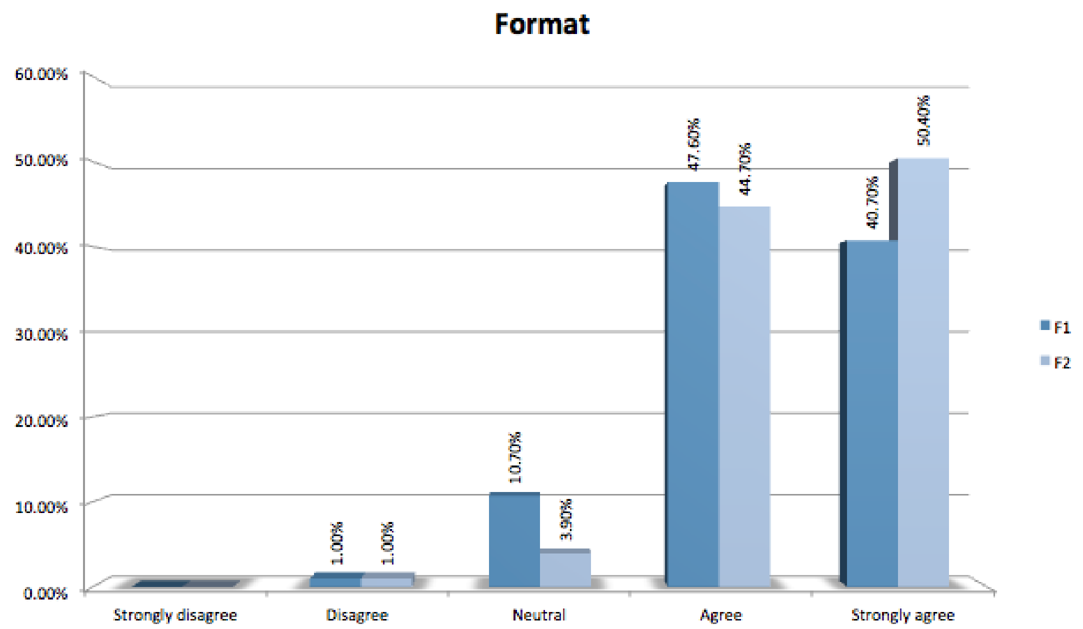


Figure 4.4 Responses (%) on format

Regarding format, its overall mean value is 4.36, consequently our questionnaire's participants were also highly contented with the BI&A systems' format. The first item of this construct, which was examining the users' perceptions towards the presentation of the systems' output (F1), scored a mean value of 4.28. Specifically, 88.3% of the respondents either agreed or strongly agreed, 10.7% were 'neutral' and 1% disagreed. F2's mean value, about whether the information provided is clear or not, is 4.45 something which is logical as 50.4% of the participants gave a 'strongly agree' answer. Moreover, 44.7% of participants agreed that the information is clear, 3.9% stayed 'neutral' and again 1% disagreed.

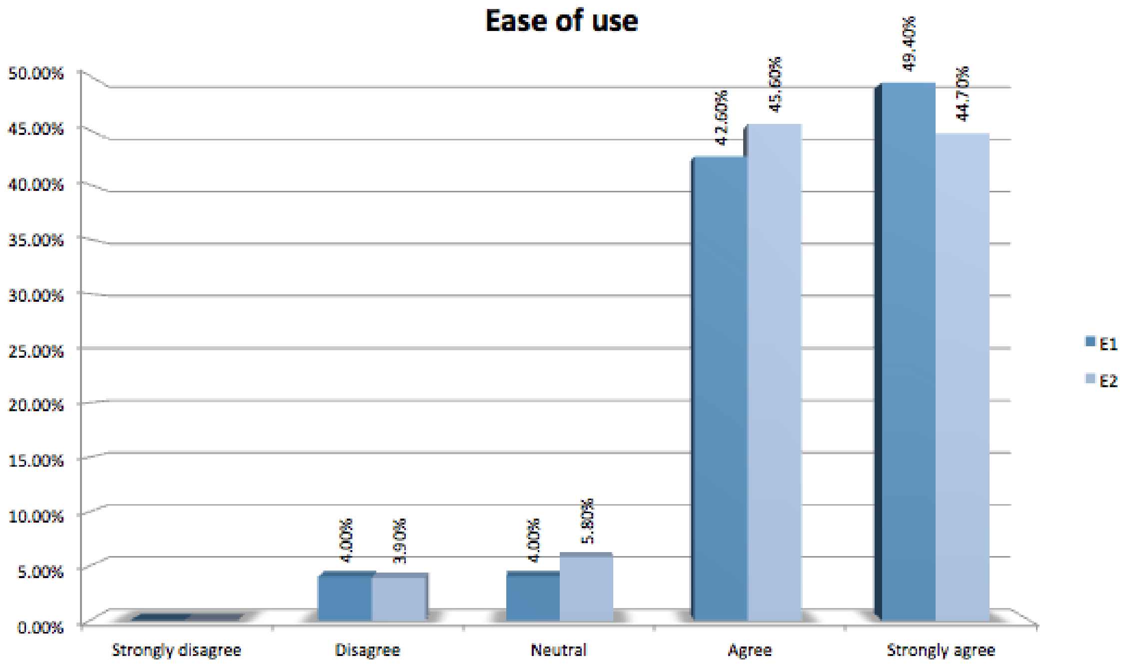


Figure 4.5 Responses (%) on ease of use

The overall mean value of ease of use is 4.34. This result implies that users have a strongly positive perception towards the BI&A systems' ease of use. The mean values of E1 and E2 are 4.38 and 4.31 respectively. In response to whether the system is user-friendly (E1), 49.4% strongly agreed, 42.6% agreed, 4% were 'neutral' and 4% disagreed. With regard to whether the descriptive BI&A system is easy to use, 44.7% strongly agreed. Those who agreed represent the 45.6%, while 5.8% gave a 'neutral' answer. Finally, 3.9% of the participants disagreed.

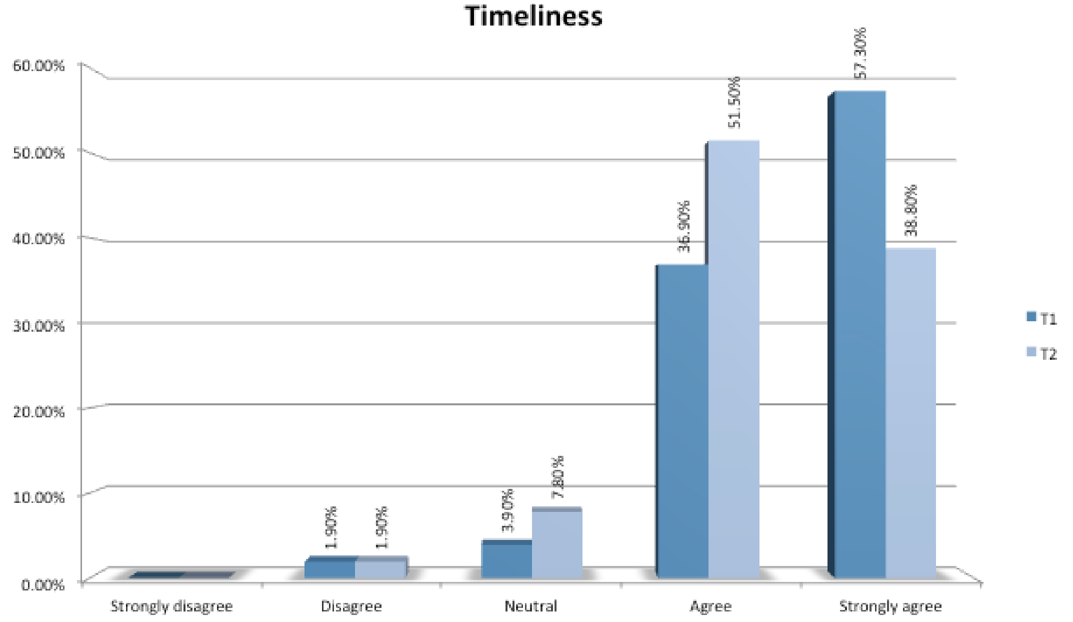


Figure 4.6 Responses (%) on timeliness

The last construct of EUCS was timeliness which scored an overall mean value of 4.38, another indicator of the undoubtedly positive perception of the participants. The mean values of the individual items used to measure timeliness are 4.50 and 4.27 respectively. Regarding whether the needed information is provided in time (T1), 57.3% of the respondents answered 'strongly agree' while 36.9% agreed. Only 3.9% stayed 'neutral' and 1.9% disagreed. Meanwhile, 38.8% strongly agreed that the information provided is up-to-date (T2) and 51.5% just agreed. Additionally, 7.8% stayed 'neutral' and 1.9% disagreed.

Training

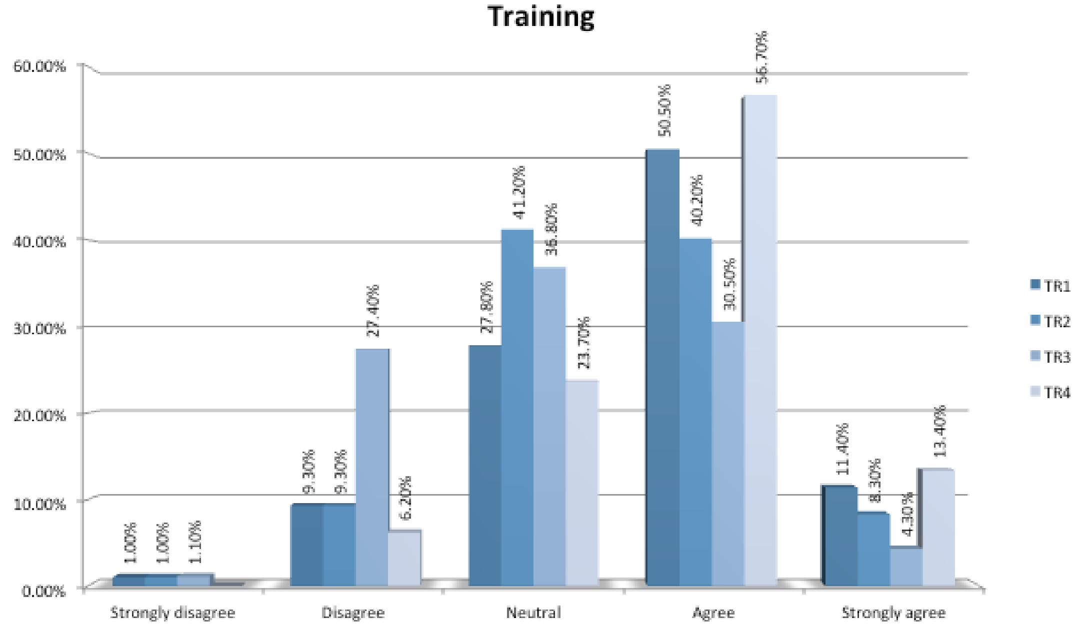


Figure 4.7 Responses (%) on training

According to Appendix III, the overall mean value of training 3.48, something which means that the respondents' attitude towards training is less positive than their attitude towards EUCS's constructs. However, the mean value is above 3.00 which serves as an indicator that most of the respondents' answers were in the range of 'neutral' and 'agree'.

The mean values of the construct's items are 3.62, 3.45, 3.09 and 3.77 respectively. In response to whether the training was sufficient (TR1) only 11.4% strongly agreed while most of the participants (50.5%) simply agreed. However, 27.8% decided to stay 'neutral' and 10.3% either disagreed or strongly disagreed. Furthermore, concerning TR2, which was examining whether the role and the objectives were clear, only 8.3% strongly agreed while the majority of the participants (81.4%) either agreed or stayed 'neutral'. Finally, 10.3% disagreed or strongly disagreed. Meanwhile, in the question about the adequacy of the training's material (TR3) only 4.3% answered 'strongly agree' whereas 69.3% either agreed or gave a neutral answer. For this question, 28.4% disagreed or strongly disagreed. For the last item (TR4), which was questioning the sufficiency of the IT support after the training, 13.4% strongly agreed, 80.4% chose to 'agree' or stay 'neutral' and 6.2% disagreed.

System Usage

Moving on to the construct of system usage, its overall mean value is 3.47.

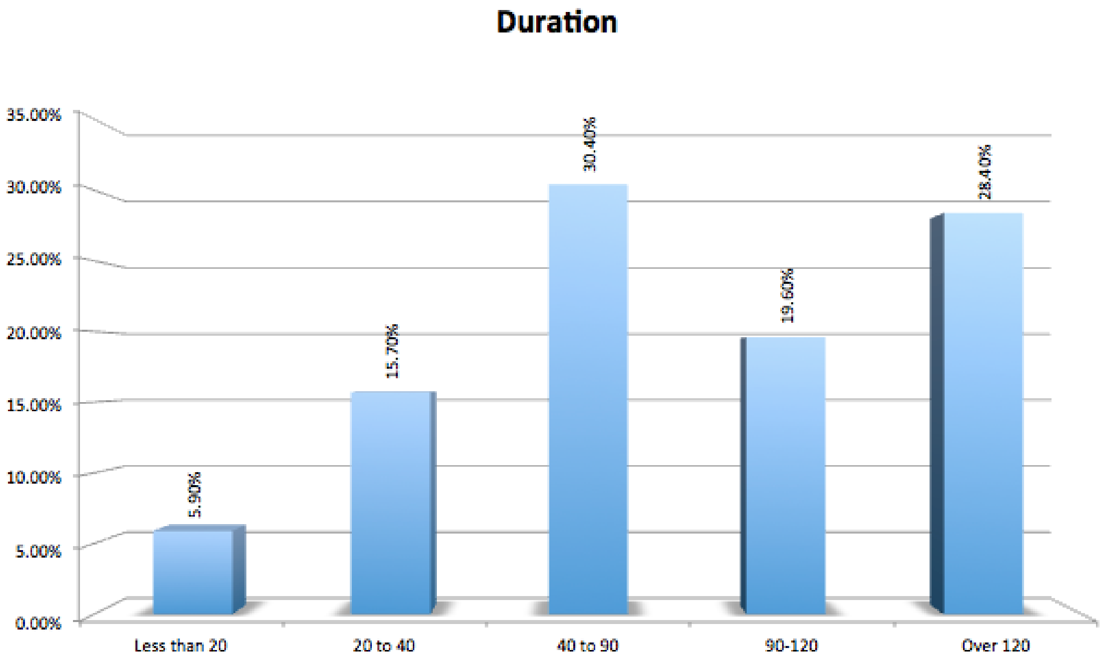


Figure 4.8 Responses (%) on duration of system's usage

The first item SU1, which was measuring the duration of the usage, scored a mean value of 3.49. According to the responses, 28.4 % of the end-users use the descriptive BI&A tools more than 120 minutes per day, 19.6% use it about 90-120 minutes per day, while the majority (30.4%) uses the tools 40-90 minutes per day, 15.7% use it about 20-40 minutes and finally, 5.9% use such tools less than 20 minutes.

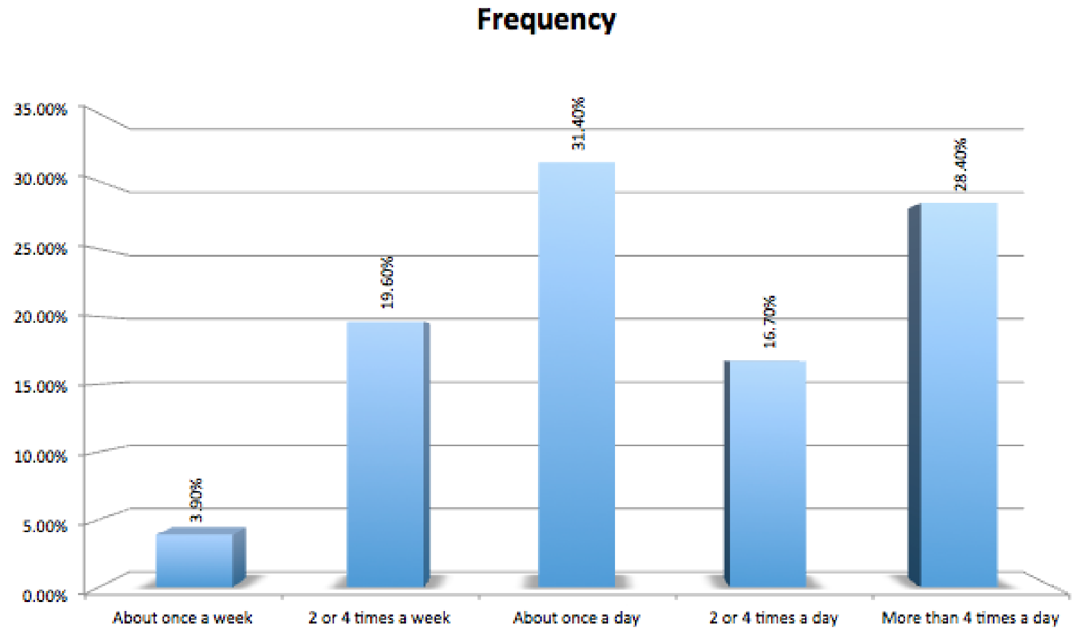


Figure 4.9 Responses (%) on frequency of system's usage

Moving on to the last item of system usage, SU2, its mean value is 3.46. In this question, the participants had to answer how frequently they use the BI&A tools. According to their answers, 28.4% make use of it more than four times a day, while 16.7% two or four times a day. The majority (31.4%) make use of it about once a day while 19.6% use it two or four times per week. Finally, the 3.9% of the participants use it about once a week.

UCI

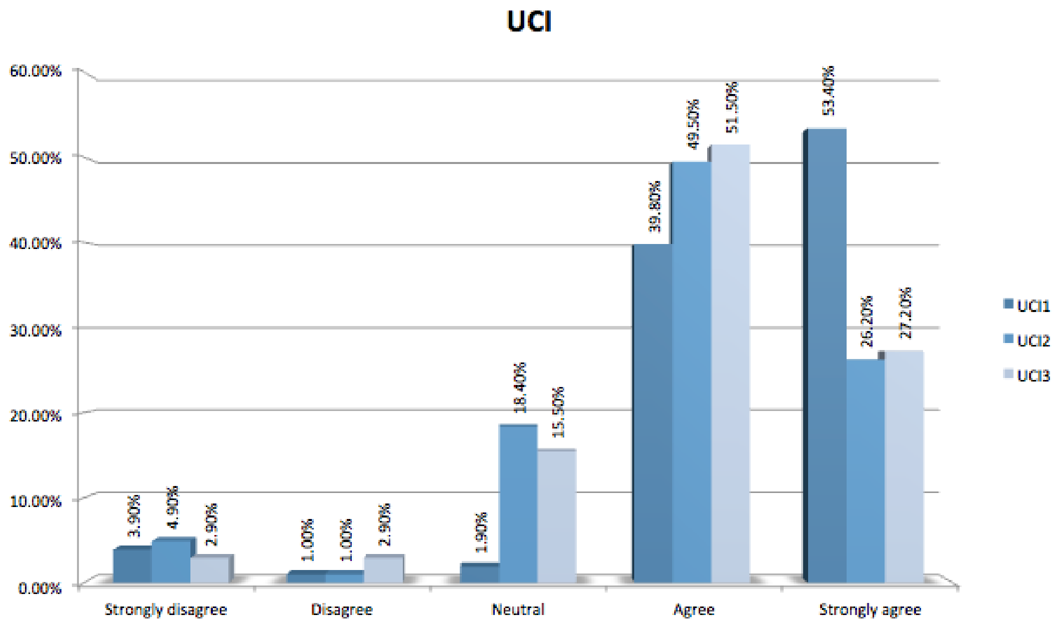


Figure 4.10 Responses (%) on UCI

Our last construct, which was measuring the UCI, scored a mean value of 4.1, which is an evidence of users' positive attitude towards UCI. Each item of the construct had a mean value of 4.38, 3.91 and 4.0 respectively. Regarding UCI1, which was measuring the users' intention to continue using the BI&A system than discontinue its use, the majority of the participants (93.2%) either agreed or strongly agreed, 1.9% chose to stay 'neutral' while 4.9% either disagreed or strongly disagreed. In response to the second item (UCI2), which was measuring whether users' would like to continue using the BI&A system than use alternative means, 26.2% strongly agreed, while 49.5% agreed. 18.4% of the respondents answered 'neutral', while 5.9% either disagreed or strongly disagreed. Finally, UCI3, which was measuring users' unwillingness of stop using the system, had 78.7% 'strongly agree' and 'agree' answers while 15.5% stayed 'neutral'. Only 5.8% were those that either disagreed or strongly disagreed.

4.2.3 Path analysis

Moving on to path analysis, it was conducted with the use of SEM technique (AMOS). Through this analysis we could test our proposed hypotheses and measure the coefficients within our proposed model. However, before moving to the path analysis of our proposed model, we present the path analysis of the EUCS model in Figure 4.11. According to this analysis, content, accuracy, format, ease of use and timeliness are characterized by high R^2 values equal to 81.3%, 73%, 80.9%, 81.9% and 72.1% respectively, which explains the degree of variance of the independent variable to the dependent one. What is more, the analysis indicated high coefficients among EUCS and its constructs with values varying from βT=0.849 to βE=0.905. These results serve as a confirmation of the EUCS model's robustness.

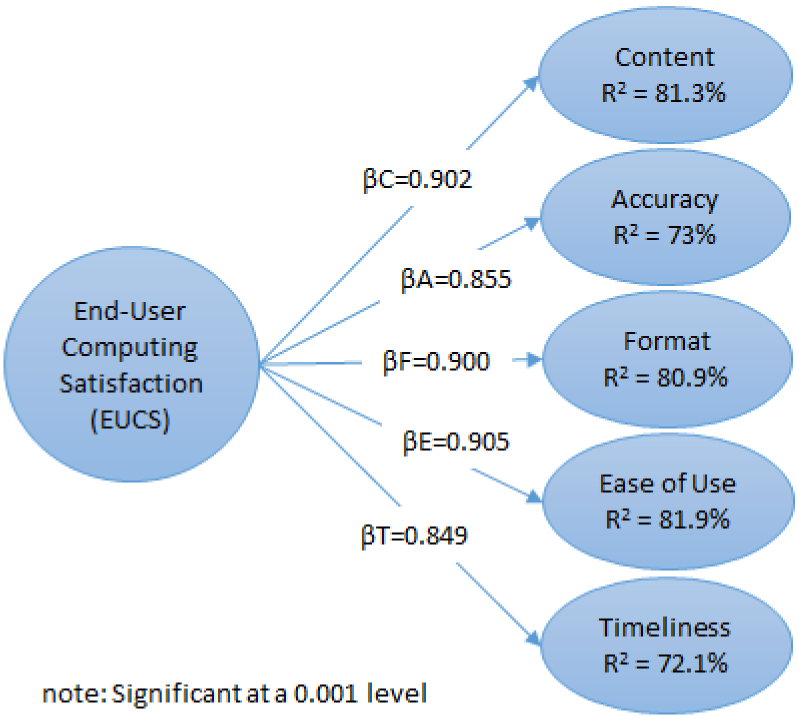


Figure 4.11 Path analysis of EUCS model in AMOS

After conducting the path analysis of EUCS model, we are moving on to the path analysis of the proposed model. Our results are presented below, in Figure 4.12, where one can see the relations and path coefficients visually (for more details see Appendix V).

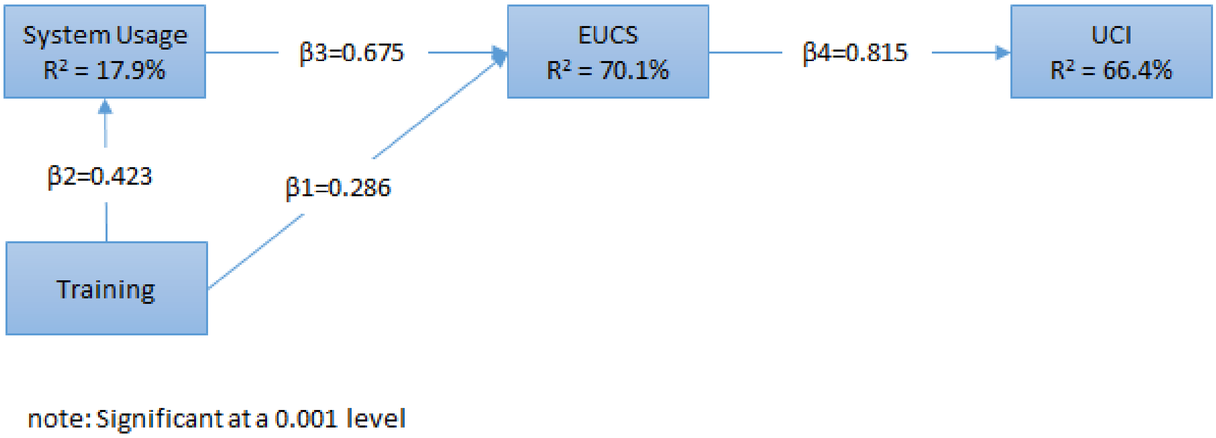


Figure 4.12 Path analysis of the proposed model in AMOS

The hypotheses which were tested are represented by the bold lines with the arrows. The directions of the arrows show the direction from the independent to the dependent variables and represent the relationships existing in our model. All of the presented relationships are statistically significant at a 0.001 level and all of our hypotheses are supported. Additionally, the numbers which are displayed in the middle of the bold lines are standardized path coefficients (Beta/β) which show the degree of influence that the independent variables have on the dependent ones. A positive number is an indicator of a positive influence while a negative one would mean the opposite. Finally, the R^2 value, in the dependent variables of system usage, EUCS and UCI, is an indicator of the degree of variance that can be explained by their independent variables.

Furthermore, since our proposed model contains three regressions, we decided to make a table (Table 4.3) in order to summarize the dependent and independent variables in each one, and provide a more clear view of our results. Except of the relationships between the variables, the values of R^2 are also displayed.

Table 4.3 Summary of regressions

Path Analysis	Independent Variables	Dependent Variables	R^2
Regression 1	Training	System Usage	17.9%
Regression 2	Training System Usage	EUCS	70.1%
Regression 3	EUCS	UCI	66.4%

Regression 1

In the first regression, a hypothesis was tested (H2) which addresses the relationship between training and system usage. As it is shown in Figure 4.12, the independent variable of training has a positive effect on the dependent variable of system usage, with $\beta2=0.423$ which is significant at a 0.001 level, and thus it supports H2. Hence, if the end-user has been trained, it is more likely to have higher system usage in the future. Moreover, training can explain the 17.9% of the variation that the variable system usage can take.

Regression 2

The second regression explains the relationship of the dependent variable EUCS with the independent variables of training and system usage. There are two hypotheses that were tested here, namely H1 and H3. Both of them were resulted as positively affecting the EUCS, with $\beta1=0.286$ for training and $\beta3=0.765$ for system usage, with a significant level at 0.001 for both. Hence, if the end-user was trained to use the descriptive BI&A system and has high frequency and duration of system usage, it is more likely to be satisfied with the BI&A system in use. Even if training has a weaker influence on EUCS than system usage, something which can be partially explained by training's indirect influence through system usage in regression 1, both hypotheses are supported. Additionally, training and system usage can explain the variation of the dependent variable, EUCS, at 70.1%.

Regression 3

In our last regression, EUCS acts as an independent variable (in contrast to regression 2). As it is shown in Table 4.3, the dependent variable in this regression is UCI. Hypothesis number four is the one that determines the relationship between these two constructs. According to the results that are presented in Figure 4.12, EUCS has a very positive effect on UCI, with $\beta4=0.815$ and significant level at 0.001, consequently H4 is supported. Therefore, the higher the degree of EUCS of the end-user, the higher is the end-user's intention to keep using the descriptive BI&A system. Finally, EUCS can explain the variation of the dependent variable UCI at 66.4%.

The results of our findings though the path analysis are summarized in Table 4.4. All of the four hypotheses are supported.

Table 4.4 Test results

Path and code	Hypothesis	Results
TR → EUCS	H1	Supported
TR → SU	H2	Supported
SU → EUCS	H3	Supported
EUCS → UCI	H4	Supported

5 Discussion

5.1 EUCS

According to the results of the descriptive analysis, end-users of descriptive BI&A tools have undoubtedly very strong positive attitudes on all of the EUCS model's constructs. This is an indicator of the BI&A systems vendors' maturity, something which is logical if we take into consideration the fact that BI&A systems are in the spotlight at least for the last 20 years. Moving on to the constructs that mostly influence EUCS, ease of use, content and format come first with accuracy and timeliness following. Except of the fact that these results confirm the model's robustness, as it has already been mentioned above, they also confirm/contradict to previously conducted studies.

In Hou's (2012) study, content was the second factor with the most influence on EUCS and format the third, like in our study, although accuracy came first. Timeliness came fourth and ease of use last in the row. On the other hand, a study conducted in the context of Internet banking presented completely different results with format coming first and timeliness, ease of use, accuracy and content following (Marakarkandy & Yajnik, 2013). These differences in the findings do not lower the model's validity, as they may derive from users' different perceptions arising due to different backgrounds. What is more, the context of the study itself may be another reason for these differences.

As we move to the hypotheses that were tested in our study, a positive EUCS relationship with UCI was confirmed. In particular, EUCS was found to have a strong influence on UCI (β=0.815). This result also confirms the results of prior conducted studies. Bhattacherjee (2001) who was one of the first that mentioned continuance intention as term, confirmed the positive relationship (β=0.567) between satisfaction and continuance intention. Meanwhile, Chang et al. (2015) came up with the same result in an LTC context (β=0.645). Finally, Chou and Chen (2009) confirmed a positive relationship (β=0.841) among satisfaction and continuance intention in an ERP context too. Consequently, we can claim that EUCS influences in a high degree users' UCI.

In order to sum up, EUCS is once again validated through our study and is proven to have a strong influence on UCI in the context of descriptive BI&A systems. This means that the more satisfaction perceived, the more are the chances that end-users will continue using the descriptive BI&A system.

5.2 Training

Regarding training, by examining the answers of the participants in our questionnaire, we find a positive but not that strong attitude. This indicates that training in companies/organisations still needs further improvements. These improvements could be translated into better preparation of the trainings' material, more days of training and more clear training objectives. The degree of IT support after training could also be further increased, even though this was the question that received the most positive answers in our questionnaire.

Moving on to the posed hypotheses, in our proposed model training was presented in two of them. Firstly, we examined if training has a positive relationship with EUCS. By conducting our analysis, we confirmed this relationship (β=0.286). This result also serves as a confirmations of previous studies where the same relationship was tested. Aggelidis and Chatzoglou (2012) had also found a positive relationship (β=0.77) among these constructs. The difference in the degree of influence could be explained by the different study settings as well as the differences in the proposed models. Moreover, Dezdar and Ainin (2011) also confirmed this relationship (β=0.618) in an ERP context. The differences here could also exist because training was combined with the level of users' education.

Our second hypothesis was examining the relationship between training and system usage. A positive association between these two constructs was also found (β=0.423). This result comes in contrast to Rouibah et al. (2009) who only confirmed an indirect positive relationship between training and system usage as, according to their results, training was affecting the usage only if the system was perceived as useful by its end-users.

Consequently, we could come up with the result that generally users of descriptive BI&A systems tend to have a higher level of EUCS if a proper training session has been conducted before the using the system. Furthermore, training affects positively the usage of a descriptive BI&A system. This is an evidence that companies/organisations need to invest more on trainings as their impact has been confirmed -at least in a descriptive BI&A context-.

5.3 System Usage

The results of the descriptive analysis concerning system usage revealed a generally positive attitude of the users. Regarding systems' usage, almost half of the participants (48%), use the descriptive BI&A tools for more than 90 minutes each week, something which is logical if we also take into consideration the vital role that such tools play in companies and organisations. This is a result that is also supported by Hou's (2012) study even though in his study the percentage was even bigger.

Moving on to the systems' frequency of usage, the results revealed that most of the users make use of descriptive BI&A tools about once a day with the answer 'more than 4 times a day' coming next. These results confirm once again the importance of such tools. In Hou's study, the largest proportion of users were using the tools more than four times per day.

These differences between the two studies could be attributed to the differences in the level of elapsed time since the BI&A systems' adoption, as well as to users' higher maturity towards such tools, especially if we take into consideration the fact that most of them (in Hou's (2012) study) had more than five years of experience.

Within our proposed model, the hypothesis that was tested regarding system usage was one. Specifically, we examined if a positive relationship exists between system usage and EUCS. According to our results, this relationship was confirmed (β=0.675). Consequently, higher level of descriptive BI&A systems' usage leads to higher levels of EUCS. This result is also a confirmation of Hou's (2012) (β=0.334) as well as Rouibah's et al. (2009) (β=0.34) results. Therefore, we can claim that the more users make use of BI&A system, the more are the chances that they will be more satisfied. The reason behind this relationship could be that, by using a system, users stop being afraid of an unknown system, learn how it can make their job easier and better and so a positive attitude towards the system is achieved.

To summarize, the more employees of a company/organisation make use of a descriptive BI&A system, the more satisfied they feel will the system itself. As a result, companies/organisations should find ways to make their users stop being afraid of systems, through activities, such as training, and make sure that their employees make usage of the system in order to have more chances for achieving EUCS.

5.4 UCI

The last construct that was included in our proposed model was UCI. In response to the answers that we received from the questionnaires, the attitude that users have seems to be strongly positive. Therefore, their intentions are to continue using the descriptive BI&A tools than stop using them. This shows that the users have understood the importance of using such tools and perceive the use of these tools as helpful for their jobs. However, in the questions where they had to answer if they would choose another tool instead of the one that they are using, their replies were more neutral. This is something that could be attributed to users' non-familiarity with other BI&A systems.

As a consequence of the above mentioned findings, we could claim that companies/organisations should keep investing on the adoption of BI&A systems as employees seem to be positive to using them and their intentions to quit this usage are low. In addition, without aiming at a specific BI&A vendor, we assure that end-user satisfaction and intention to continue using the system results are applicable to all companies and organisations that invested or are willing to invest on any BI&A system.

5.5 The power of R^2

As discussed previously, R^2 reveals the degree of variance that the independent factor can have on the dependent one. In our study, the dependent factors were three, namely system usage, EUCS and UCI, and their R^2 values were 17.9%, 70.1% and 66.4% respectively. Accordingly, in our first relationship, the independent factor of training could explain the degree of variance at 17.9% of the dependent factor of system usage. In our second relationship, the independent factors of training and system usage could explain the degree of variance of

EUCS at 70.1%. While, in the last relationship, EUCS could explain 66.4% the degree of variance of UCI.

In the last two relationships, the value of R^2 is quite high, revealing that the independent factors represent the dependent ones with a high degree of explanatory ability. However, the first relationship reveals that training has a low degree of explanatory ability to system usage. This is probably caused by other potential factors that affect system usage and are not identified in this study.

6 Conclusion

6.1 Research questions

As has been noted, the main goal of this paper was to examine the EUCS within descriptive BI&A context and the relationship between EUCS, system usage, training and UCI. In order to achieve the purpose of the study, we formed three research questions so as to measure descriptive BI&A's end-users' perceptions. This measurement was achieved through the distribution of a questionnaire-based survey. By doing that, we were able to measure the respondents' attitudes towards factors and test the relationships (hypotheses) between those factors within our proposed model. Based on the empirical results and analysis which were conducted with the help of statistic techniques and statistical software (Excel, SPSS, AMOS) and which were presented in Chapter 4, we reached some conclusions for each one of our research questions. Consequently, our research questions were answered as follows:

Research question 1

How does training influence the system usage of descriptive BI&A systems?

After conducting this study, we came up with the result that training does have a positive influence on system usage. The end-users of descriptive BI&A tools have a positive perception towards training's effect on system usage. As a consequence, end-users that have gotten efficient training before starting using the BI&A tool, tend to use it more frequently and in larger duration than those who have not. However, the degree of variance that can be explained by this relationship is low. Consequently, we can claim that system usage has different factors that may influence it in higher degree and which have not been examined in this study.

Research question 2

How does training and system usage influence end-user's satisfaction regarding EUCS of descriptive BI&A systems?

The results of the study proved that both training and system usage have a positive effect on EUCS. System usage has a more significant one, but even so, training has also an indirect influence through system usage on EUCS. Therefore, end-users of descriptive BI&A tools that were trained and have high degree of system usage tend to be highly satisfied with the system in use.

Research question 3

How does EUCS influence the UCI of descriptive BI&A systems?

The results show that there is a significant direct positive influence of EUCS to UCI. Consequently, end-users that are highly satisfied with the descriptive BI&A tool in use, tend to have higher intentions to continue using it. Although, the degree of variance is not that strong, it is above average, confirming that the relationship is quite robust.

6.2 Implications

By conducting this study, we extended the knowledge of descriptive BI&A towards EUCS and the intention of end-users to continue using such systems, as well as the robustness that training and system usage can serve to maximise EUCS. The results of this study show that the end-users of descriptive BI&A tools are satisfied with them and intent to continue using them in the future. Thus, the practical perspective of this study is that it is offering an insight on the reasons that satisfy more the end-users of descriptive BI&A tools.

EUCS model has been proven appropriate to address the factors of satisfaction towards descriptive BI&A tools. End-users of such systems have been proven to be highly satisfied when the BI&A tool is user-friendly and easy to use, the content provided has precise and sufficient information for reporting that meets their needs, and the output of the system is in useful format with clear information. Meanwhile, accuracy and timeliness of the descriptive BI&A tools have slightly less influence on EUCS. For practical implications, EUCS has been proven to have a positive and significant influence on UCI, nonetheless not such a strong one, so there is a need to reach out other factors that may influence UCI.

In addition, the results of this study show that the higher the system usage is, the higher the EUCS will be. This means that the end-users that use the descriptive BI&A tool more frequently and in larger duration, tend to be higher satisfied than those who do not. Therefore, companies and organisations that implement BI&A tools should encourage their employees to use the system more, and probably get them influenced by the ones that do so as to maximise the beneficial promises of descriptive BI&A tools.

Given the training, the results show that it is another factor that has a positive relationship with EUCS as well as with system usage, in spite of not being a strong one for both. The existed training that companies and organisations offer up to now to their employees may not fulfil the end-users' perception towards EUCS. So maybe the training that employees get is not the appropriate one to provide them the knowledge they need so as to expand the capabilities of such systems. This indicates that companies and organisations should focus more on training so as to offer to their employees more meaningful and accurate education with sufficient training material and support. Except from that, regarding theoretical implications, there is a need for other factors that may influence EUCS and system usage to be addressed.

6.3 Limitations

Even though our aim was this study to be conducted in a perfect way, this could not happen due to practical and resource limitations. As it has already been discussed in Chapter 3 about methodology, we used a convenience sampling technique, since reaching companies turned out to be more difficult than we thought. Consequently, neither does this study cover end-users from all types of industries, nor BI&A software from all the possible vendors. This choice of non-probability sampling has also affected the external validity of the study. However, we believe that the similarities between the BI&A software as well as the similarities in the tasks that are performed in companies'/organisations' departments, regardless of the industry in which they perform, do provide a margin of generalization, at least from a conceptual perspective.

Moreover, we chose to measure users' satisfaction by using the EUCS model based on its 12 items plus 9 items that we added for measuring the factors of training, system usage and UCI. This on its own is a limitation as there are many more other models, which measure satisfaction in a different way, as well as many other factors that we could measure such as perceived usefulness and self-efficacy. Furthermore, this paper was formed around users' perceptions, something which inevitably adds a sense of subjectivity in the measurements. Additionally, the measurements happened at one point in the time so we cannot know if the respondents would give the same answers if the study was conducted today. Finally, we focused only on examining descriptive BI&A tools.

6.4 Contribution

By testing our proposed model, we have broaden the knowledge concerning descriptive BI&A. Since there is only one study examining users' satisfaction in BI&A context, the main contribution of our study is that it has shorten the literature gap of investigating end-users' satisfaction towards BI&A. This offers an insight of the end-users' perception for descriptive BI&A systems both in academia and in industry world, as inspiration can be generated for conducting further studies or understanding specific aspects of BI&A systems correspondingly. In addition, there are just a few studies examining users' perceptions regarding EUCS and UCI. Consequently, our study, which is focused in the context of descriptive BI&A, can be exploited by companies/organisations that have adopted or thinking of adopting a BI&A tool so as to overcome existing or potential problems of BI&A tool's adoption and ensure satisfaction and commitment to the tool by their end-users.

6.5 Suggestions for further study

Even though the aim of this thesis has been achieved, there is still room for research. This is a result of the study's limitations and the methodology's restrictions. Consequently, we will present some thoughts about how this paper can be further researched in different ways.

Use other model for measuring satisfaction

Regarding satisfaction, this paper uses the EUCS model in order to measure it. However, as we have already mentioned in Chapter 2, there is also the TAM and D&M's model which measure users' acceptance and IS success -including the measurement of satisfaction-. Therefore, one idea for future research would be to conduct the same study using another model.

Use other factors

In this paper, we examined how training and system usage affect EUCS, although these are only two of the factors that affect it. Further research could examine other potential factors. The same applies for the UCI.

Expand the sample size and use probability sampling

Our study, as it has already been discussed above, adopted a convenience sampling method mainly due to time and accessibility limitations. Further study with larger sample using probability sampling could be conducted. This way, the study would be improved through the improvement of its external validity.

Different sample and context

We have conducted our study with users of descriptive BI&A in UK, Sweden and Greece. Further study can be suggested with users from other countries. By doing that, we will be able to see if there are any differences - deriving from culture and/or level of BI&A's maturity in the chosen countries - in the users' perceptions. Another thought would be to conduct the same study with a focus on predictive or prescriptive BI&A or in a different computer-based application.

Longitudinal approach

Since the questionnaires were sent to the end-users at one point at the time, we cannot be sure that their answers will be the same, giving us the same results, today. It would be interesting to see the change, if any, in their perceptions as the time goes by and their experience with descriptive BI&A grows. Consequently, a longitudinal approach would be valuable.

Appendix I Research Questionnaire

Descriptive BI&A: Examining the relationships between EUCS, Training, System usage and UCI.

Hello!

We are two students studying Information Systems at Lund University of Sweden. We are writing our master thesis about Business Intelligence and Analytics (BI&A). For our thesis purposes, we would like to invite you to take part in this short survey. Your opinion and views are important to us. The questionnaire should not take longer than 10 minutes.

This survey aims to identify and test the relationships among end-user computing satisfaction (EUCS), training, system usage and usage continuance intention (UCI) in the context of descriptive BI&A. Descriptive BI&A involve standard and ad-hoc reports, queries and alerts. Consequently, your experience of using a descriptive BI&A application is important for our investigation.

Participation in this questionnaire is completely anonymous and no attempt will be made to associate you with the responses that you will provide. Please fill out the questionnaire carefully. Note that there is no right or wrong answer, please select the answer that suits you the best. You can withdraw anytime by just leaving this page. The results of this study will be included in our thesis which will published by Lund University and in that way it will be available to be read by students in Information Systems and Business Departments of Lund University and by Lund's university professional partners in the same areas.

We would appreciate it a lot if you could respond to our survey within 10 ten days. This will help us to accomplish our thesis on time.

Thanks for your support and participation!

Part one: Demographics

Kindly mark your answers from the lists by clicking on them.

1. **Gender**
   Mark only one oval.
   - ◯ Male
   - ◯ Female

2. **Department**
   Write your answer on the text box.

   ____

3. **Work position**
Mark only one oval.
- Non-management/professional staff
- Middle-level management
- Top-level management/executives

4. **Elapsed time since adoption of the BI&A system (years)**
Mark only one oval.
- Less than 1
- 1-3
- 3-5
- 5-10
- Over 10

5. **BI&A experience (years)**
Mark only one oval.
- Less than 1
- 1-4
- Over 5

6. **BI&A system's use each week (minutes)**
Mark only one oval.
- Less than 20
- 20-40
- 40-90
- 90-120
- Over 120

7. **Frequency of BI&A system's usage**
Mark only one oval.
- About once a week
- 2 or 4 times a week
- About once a day
- 2 or 3 times a day
- More than 4 times a day

Part two: Degree questions about EUCS, Training, System usage and UCI

Kindly mark your questions by clicking on the button.

8. **End User Computing Satisfaction**
Mark only one oval per row.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
The BI&A system provides the precise information I need					
The BI&A's information content meets my needs					
The BI&A system provides reports that seem to be just about exactly what I need					
The BI&A system provides sufficient information					
The BI&A system is accurate					
I am satisfied with the accuracy of the BI&A system					
The BI&A's output is presented in a useful format					
The information is clear					
The BI&A system is user-friendly					
The BI&A system is easy to use					
I get the information I need in time					
The BI&A system provides up-to-date information					

9. **Training**
In case that training did not take place, please move to the next section.
Mark only one oval per row.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
The availability of training was sufficient					
My role and the objectives before training were clear					
The course material during training was adequate					
The IT support after training was sufficient					

10. **Usage Continuance Intention**
Mark only one oval per row.

	Strongly disagree	Strongly agree	Neutral	Agree	Strongly agree
I intend to continue using the BI&A system than discontinue its use					
My intentions are to continue using the BI&A system than use any alternative means					
Even if I could I would not like to discontinue the use of the BI&A system					

Appendix II Summary of demographics

Categories	Range	Frequency	Percentage
Gender	Male	55	53.4%
	Female	48	46.6%
Work position	Non-management/professional staff	57	55.3%
	Middle-level management		
	Top-level management/executive	38	36.9%
		8	7.8%
Elapsed time since adoption of the BI&A system	Less than 1	9	8.7%
	1-3	53	51.5%
	3-5	32	31%
	5-10	7	6.8%
	Over 10	2	2%
BI&A experience	Less than 1	35	34%
	1-4	54	52.4%
	Over 5	14	13.6%

Appendix III Summary of descriptive measurement scales

Construct items	Code	Mean	Std. Deviation
Content (C)		4.38	
The BI&A system provides the precise information I need.	C1	4.24	0.552
The BI&A's information content meets my needs.	C2	4.41	0.585
The BI&A system provides reports that seem to be just about exactly what I need.	C3	4.46	0.590
The BI&A system provides sufficient information.	C4	4.43	0.604
Accuracy (A)		4.27	
The BI&A system is accurate.	A1	4.19	0.687
I am satisfied with the accuracy of the BI&A system.	A2	4.35	0.652
Format (F)		4.36	
The BI&A's output is presented in a useful format.	F1	4.28	0.692
The information is clear.	F2	4.45	0.622
Ease-of-use (E)		4.34	
The BI&A system is user-friendly.	E1	4.38	0.746
The BI&A system is easy to use.	E2	4.31	0.754
Timeliness (T)		4.38	
I get the information I need in time.	T1	4.50	0.670
The BI&A system provides up-to-date information.	T2	4.27	0.689
Training (TR)		3.48	
The availability of training was sufficient.	TR1	3.62	0.847
My role and the objectives before training were clear.	TR2	3.45	0.817
The course material during training was adequate.			

The IT support after training was sufficient.	TR3 TR4	3.09 3.77	0.888 0.757
System usage (SU)		3.47	
How much time do you spend each week using the BI&A system?	SU1	3.49	1.225
At present how often do you use the BI&A system?	SU2	3.46	1.208
UCI		4.10	
I intend to continue using the BI&A system than discontinue its use.	UCI1	4.38	0.898
My intentions are to continue using the BI&A system than use any alternative means.	UCI2	3.91	0.961
Even if I could I would not like to discontinue my use of the BI&A system.	UCI3	4.00	0.856

Appendix IV Summary of descriptive statistics

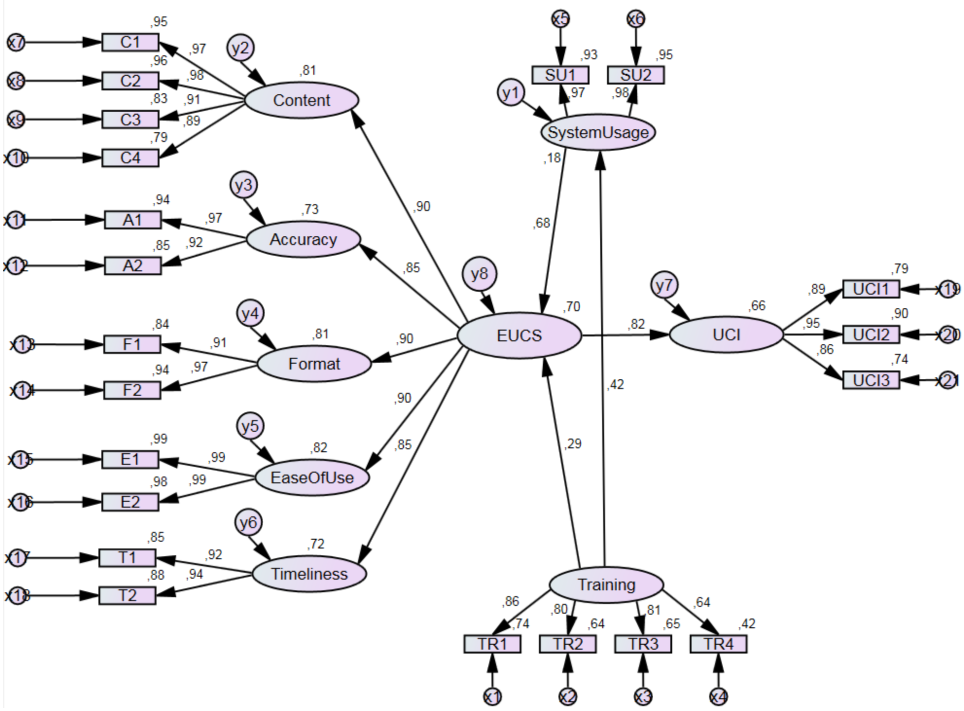
Constructs	Items	Measures	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Content (C)	C1	Freq.	0	0	3	54	46
		(%)	0%	0%	2.9%	52.4%51	44.7%
	C2	Freq.	0	0	5	49.5%46	47
		(%)	0%	0%	4.9%	44.7%47	45.6%
	C3	Freq.	0	0	5	45.6%	52
		(%)	0%	0%	4.9%		50.4%
	C4	Freq.	0	0	6		50
		(%)	0%	0%	5.8%		48.6%
Accuracy (A)	A1	Freq.	0	0	16	51	36
		(%)	0%	0%	15.5%	49.5%47	35.0%
	A2	Freq.	0	0	10	45.6%	46
		(%)	0%	0%	9.7%		44.7%
Format (F)	F1	Freq.	0	1	11	49	42
		(%)	0%	1%	10.7%	47.6%46	40.7%
	F2	Freq.	0	1	4	44.7%	52
		(%)	0%	1%	3.9%		50.4%
Ease of use (E)	E1	Freq.	0	4	4	44	51
		(%)	0%	4%	4%	42.6%47	49.4%
	E2	Freq.	0	4	6	45.6%	46
		(%)	0%	3.9%	5.8%		44.7%
Timeliness (T)	T1	Freq.	0	2	4	38	59
		(%)	0%	1.9%	3.9%	36.9%53	57.3%
	T2	Freq.	0	2	8	51.5%	40

		(%)	0%	1.9%	7.8%		38.8%
Training (TR)	TR1	Freq.	1	10	28	52	12
		(%)	1%	9.3%	27.8%	50.5%41	11.4%
	TR2	Freq.	1	10	42	40.2%32	9
		(%)	1%	9.3%	41.2%	30.5%58	8.3%
	TR3	Freq.	1	27	38	56.7%	5
		(%)	1%	27.4%	36.8%		4.3%
	TR4	Freq.	0	6	25		14
		(%)	0%	6.2%	23.7%		13.4%
UCI	UCI1	Freq.	4	1	2	41	55
		(%)	3.9%	1%	1.9%	39.8%51	53.4%
	UCI2	Freq.	5	1	19	49.5%53	27
		(%)	4.9%	1%	18.4%	51.5%	26.2%
	UCI3	Freq.	3	3	16		28
		(%)	2.9%	2.9%	15.5%		27.2%

Constructs	**Items**	**Measures**	**Less than 20**	**20-40**	**40-90**	**90-120**	**Over 120**
System usage (SU)	SU1	Freq. (%)	6 5.9%	16 15.7%	32 30.4%	20 19.6%	29 28.4%

Constructs	**Items**	**Measures**	**About once a week**	**2 or 3 times a week**	**About once a day**	**2 or 3 times a day**	**More than 4 times a day**
System usage (SU)	SU2	Freq. (%)	4 3.9%	20 19.6%	33 31.4%	17 16.7%	29 28.4%

Appendix V Hypotheses testing and results



Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
SystemUsage	<---	Training	,423
EUCS	<---	Training	,286
EUCS	<---	SystemUsage	,675
UCI	<---	EUCS	,815
Content	<---	EUCS	,902
Accuracy	<---	EUCS	,855
Format	<---	EUCS	,900
EaseOfUse	<---	EUCS	,905
Timeliness	<---	EUCS	,849

TR4	<---	Training	,645
TR3	<---	Training	,807
TR2	<---	Training	,802
TR1	<---	Training	,862
SU1	<---	SystemUsage	,966
SU2	<---	SystemUsage	,976
C4	<---	Content	,889
C3	<---	Content	,912
C2	<---	Content	,980
C1	<---	Content	,973
A2	<---	Accuracy	,921
A1	<---	Accuracy	,968
F2	<---	Format	,967
F1	<---	Format	,915
E2	<---	EaseOfUse	,988
E1	<---	EaseOfUse	,993
T2	<---	Timeliness	,939
T1	<---	Timeliness	,922
UCI1	<---	UCI	,887
UCI2	<---	UCI	,948
UCI3	<---	UCI	,860

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
SystemUsage	<---	Training	1,000				
EUCS	<---	Training	1,000				
EUCS	<---	SystemUsage	1,000				
UCI	<---	EUCS	,363	,038	9,433	***	
Content	<---	EUCS	,324	,027	12,040	***	
Accuracy	<---	EUCS	,338	,031	11,072	***	
Format	<---	EUCS	,398	,028	13,990	***	
EaseOfUse	<---	EUCS	1,000				
Timeliness	<---	EUCS	,366	,032	11,406	***	
TR4	<---	Training	,818	,123	6,638	***	
TR3	<---	Training	1,197	,136	8,818	***	
TR2	<---	Training	1,000				
TR1	<---	Training	1,222	,128	9,553	***	
SU1	<---	SystemUsage	1,000				
SU2	<---	SystemUsage	1,000				
C4	<---	Content	1,000				
C3	<---	Content	1,028	,070	14,584	***	
C2	<---	Content	1,197	,067	17,971	***	
C1	<---	Content	1,109	,063	17,557	***	
A2	<---	Accuracy	1,000				
A1	<---	Accuracy	1,162	,069	16,878	***	
F2	<---	Format	1,000				
F1	<---	Format	,985	,057	17,194	***	
E2	<---	EaseOfUse	,887	,020	44,122	***	

E1	<---	EaseOfUse	1,000				
T2	<---	Timeliness	1,000				
T1	<---	Timeliness	,939	,063	14,995	***	
UCI1	<---	UCI	1,106	,091	12,199	***	
UCI2	<---	UCI	1,328	,097	13,638	***	
UCI3	<---	UCI	1,000				

Squared Multiple Correlations: (Group number 1 - Default model)

			Estimate
SystemUsage			,179
EUCS			,701
UCI			,664
Timeliness			,721
EaseOfUse			,819
Format			,809
Accuracy			,730
Content			,813
UCI3			,739
UCI2			,899
UCI1			,787
T1			,850
T2			,882
E1			,985
E2			,976
F1			,837
F2			,936

A1			,937
A2			,847
C1			,946
C2			,961
C3			,831
C4			,790
SU2			,953
SU1			,934
TR1			,743
TR2			,644
TR3			,651
TR4			,416

Correlations: (Group number 1 - Default model)

			Estimate
Training	<-->	SystemUsage	,013
Content	<-->	Accuracy	,478
Content	<-->	Format	,521
Content	<-->	EaseOfUse	,232
Content	<-->	Timeliness	,558
Content	<-->	Training	,422
Content	<-->	SystemUsage	,107
UCI	<-->	Content	,474
Accuracy	<-->	Format	,445
Accuracy	<-->	EaseOfUse	,126
Accuracy	<-->	Timeliness	,274

Accuracy	<-->	Training	,375
Accuracy	<-->	SystemUsage	,243
UCI	<-->	Accuracy	,521
Format	<-->	EaseOfUse	,274
Format	<-->	Timeliness	,515
Format	<-->	Training	,478
Format	<-->	SystemUsage	,186
UCI	<-->	Format	,284
EaseOfUse	<-->	Timeliness	,146
EaseOfUse	<-->	Training	,334
EaseOfUse	<-->	SystemUsage	,141
UCI	<-->	EaseOfUse	,236
Timeliness	<-->	Training	,291
Timeliness	<-->	SystemUsage	,147
UCI	<-->	Timeliness	,327
UCI	<-->	Training	,201
UCI	<-->	SystemUsage	,156

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