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Study of the criteria for the adoption of interfaces in decision support systems

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Study of the criteria for the adoption of interfaces in decision support systems

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Abstract

This paper analyzes the different factors predicting the use of a BI dashboard using the technology acceptance model developed by Davis and adapting it to the present topic. The hypotheses proposed here are based on two theories in the literature, namely the theory of hedonic information systems and the cognitive theory of multimedia learning. A survey concerning the intention to use dashboards was conducted on a sample of people with management skills and the analysis of the results showed the crucial importance of perceived usefulness as well as perceived enjoyment, which confirms the presence of a hedonic character in the dashboards of BI systems. The analysis also shows the role of the perceived ease of use for the acceptance of a dashboard. This paper then discusses these results and their implications, and also discusses the various limitations of the present study.

Contents

1 Introduction

The term Business Intelligence has been around for more than 20 years and has been gaining in importance among economic players. The term "Business Intelligence System" (BIS) is a commonly used term to designate a set of tools, software and techniques - arranged in a global architecture - used in a company to identify, integrate, prepare, display, analyze and even exploit data from multiple and often heterogeneous sources. In other words, a business intelligence system consists of a series of engineering methods and software used together to provide an integrated and automated view of an organization's operations. Its purpose is to help managers understand the environment and support them in making strategic decisions. The user's needs must therefore be at the center of an effective BI system.

BI systems have long been recognized as an important success factor, necessary to create or maintain a competitive advantage in small and large companies. They are designed to facilitate the processing of data and information along the information value chain (Glazer, 1993)[1], giving business managers the information they need to make decisions and take necessary actions.

The design and implementation of business intelligence systems remains a significant challenge for organizations in general, with a high risk of failure and potentially high rewards. Companies are devoting more and more resources to BIS implementation. As the amount of resources invested in these systems increases, the need for assurances of their overall success becomes more apparent. Specifically, there is a risk that considerable effort will be spent on implementing a quality BIS that will not actually be leveraged to its full potential, i.e., the system will be successfully implemented but will not be adopted by end users. There are many reasons for this issue and it is critical for BI system designers to understand these factors in order to create a product that is not only useful, but also used in practice by the user. It is on these factors that this paper will focus.

2 Adoption of business intelligence systems

2.1 BI Systems Adoption Model

The problem of technology adoption is not new and has been addressed in the literature on numerous occasions. The "Technology Acceptance Model" (TAM) defined by Davis in 1989 is very often used to estimate the chances of adoption of a new technology by a user. Year after year, the TAM has been adapted and enriched in many ways, to fit the specificities of different types of information systems (see [Lee2003][2] for a review of these extensions). According to Lee, there are several contributions that attempt to extend the technology acceptance model to assess the likelihood of adoption of a decision support system (DSS) or a spreadsheet (which is commonly used to support decisions in companies).

Dashboards are defined as user interfaces that organize and present information in a way that is easy to read and interpret [Palpanas2007][3]. They typically include a set of indicators, graphs, and charts as well as interactive features to provide decision makers with a consistent yet flexible representation of a company's situation. However, a comprehensive BIS can be compromised by various factors, such as visuals that are not convincing enough, presentation that is not clear enough, or the impression that the system is not useful enough to be used. In this paper, we will consider that the user's intention of use is a strong predictor of the use he will make of the complete system. The objective here is to extend the TAM to the adoption of BI dashboards. Indeed, to our knowledge, there is no specific extension for this.

2.2 The adoption of business intelligence systems

From a theoretical perspective, the standard assumption in the BIS literature is that dashboards act as a remedy to the problem of information overload by providing "a complete package for performance management, incorporating various concepts and applications such as strategy maps,

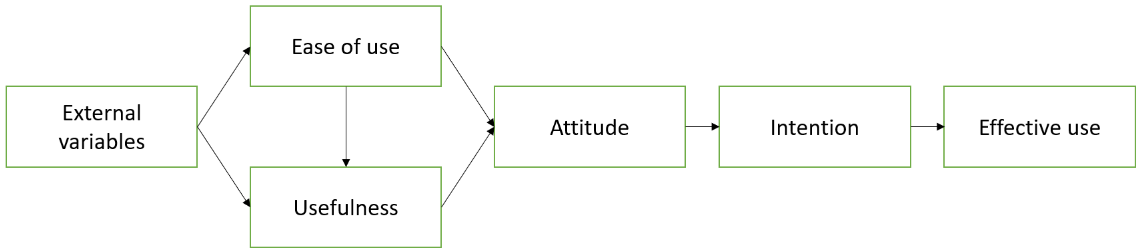

Figure 2.1: Technology Acceptance Model defined by Davis

dashboards, and BI into a manageable solution" [Yigitbasioglu, 2012][4]. In other words, the role of any BIS dashboard is to turn the risk of overload into opportunity [Keim, 2006][5]. This assumption is based on the fact that the user of the dashboard will be able to grasp all the information and will not be overloaded by the amount of information, indicators, graphs or maps.

In practice, however, designing BIS dashboards that actually reduce the risk of information overload is a complex activity. Dashboard designers must decide which visual elements to include and, more importantly, which facts and dimensions of a business those visual elements should represent. To assist BIS designers in this selection, various models and methods have been defined to systematize the design of data warehouses [Golfarelli, 1998; Horkoff, 2012][6][7], data visualizations (Chi, 2000; Lurie2007)[8][9], key performance indicators [Kaplan, 1992][10] and of course dashboards (Eckerson, 2010; Brath, 2004)[11][12]. All these approaches agree in their recommendation to include more information; more indicators in the Balanced Scorecard [Kaplan, 1992][10], more facts and dimensions in the Business Intelligence model [Horkoff, 2012][7] or the Dimension Fact model [Golfarelli, 1998][6], more visuals and filters in the design of effective dashboards [Eckerson2010][11]. Few, if any, make distinctions in the importance of the different loads to be displayed in the dashboard. This includes the risk of reaching an unnecessary information overload in the BI system.

In our view, it is quite reasonable to assume that too much information displayed in a dashboard, even if it is presented as visuals and controlled by filters and other exploration mechanisms, increases the risk that the user will be confused when making a decision and will not properly exploit the dashboard. The impact of these dashboard overloads spills over into the very problem of BIS adoption; a dashboard that fails to support decision makers has a high risk of being underutilized by decision makers, who will turn to more traditional (but less integrated) sources of information outside of BIS. This can result in a lower-than-expected return on investment for BIS, or even a situation where BIS is not used at all, with obvious financial and operational consequences. This shows the importance of knowing which elements to display in the dashboard in order to be efficient without causing information overload.

2.3 Research Questions

The preceding discussion leads us to define the following research questions:

- What factors predict dashboard use?
- How important are these factors to dashboard adoption?

In order to answer these two research questions, a model is constructed that incorporates two existing theories, namely the hedonic information system theory and the cognitive theory of multimedia learning. This model includes different hypotheses that are developed in section 4. In order to test the proposed hypotheses and to validate our research model, we conducted an experiment in which dashboards in which we voluntarily inserted variations in terms of quantity and characteristics of information were presented to the participants. We asked participants to manipulate a randomly assigned dashboard and to answer a questionnaire. The results of the measurement model and structural equation model analysis are presented in Section 6. Finally, we discuss our results and conclude this paper.

3 Theoretical Background

In this section, we present the two theoretical bases around which we build our study, namely the hedonic information system theory and the cognitive theory of multimedia learning. These two theories will allow us to develop the hypotheses of our research studying the factors predicting the behavioral intention to use BI dashboards.

We also present different models used in the literature to define the acceptance of a technology. This part does not aim at making an exhaustive review of these models but rather at understanding the different versions of existing models. The central model of this section is the TAM, a model that has been modified many times over to be applied to various technologies, and several versions of it are presented.

3.1 The theory of the hedonic information system

A hedonic information system finds its value in the pleasure that the user experiences while using the system, as opposed to a purely utilitarian system where the value is purely instrumental, coming for example from the features offered by the system to increase performance (Chesney, 2006)[13]. Van der Heijden (Van der Heijden, 2004)[14] proposed the hedonic information system theory, according to which the nature of the system plays an important role in user acceptance. The author identified three predictors of BIU (behavioral intention of use): perceived enjoyment, perceived usefulness and perceived ease of use. His study showed that perceived enjoyment and perceived ease of use are stronger determinants of intention to use than perceived usefulness when dealing with hedonic systems. The author highlights two main implications for research: (i) the purpose of the system (hedonic or utilitarian) will influence the predictive power of the determinants; and (ii) perceived ease of use is critically important for user acceptance of hedonic information systems. In essence, we believe that BISs are dual systems (Chesney, 2006)[13]-both pleasure and productivity oriented-at least for the following reasons:

- They aim to display serious - and relatively boring - content (data, reports, tables) in a more exciting and pleasing layout (visuals with lots of color) ;
- They are intended to offer great flexibility to users, who can interact smoothly with the data and visuals;
- They intend to hide from the end user all the complexity of the BIS architecture, leaving only the responsibility of making a final business decision to the end users who can easily analyze and exploit the information;
- They aim to speed up the decision-making process and reduce the impact of data quality issues on the decision-making process.

These findings led us to believe that the consideration of hedonic information systems theory was important if one wanted to explain the BIU of a dashboard. Nevertheless, it is obvious that the utilitarian part of the dashboards can in some cases take over the hedonic part, thus drastically changing the predictors of technology adoption. In these cases, the assumption that ease of use and perceived enjoyment are more crucial in predicting technology adoption than perceived usefulness would no longer be valid since the system will have lost its hedonic component.

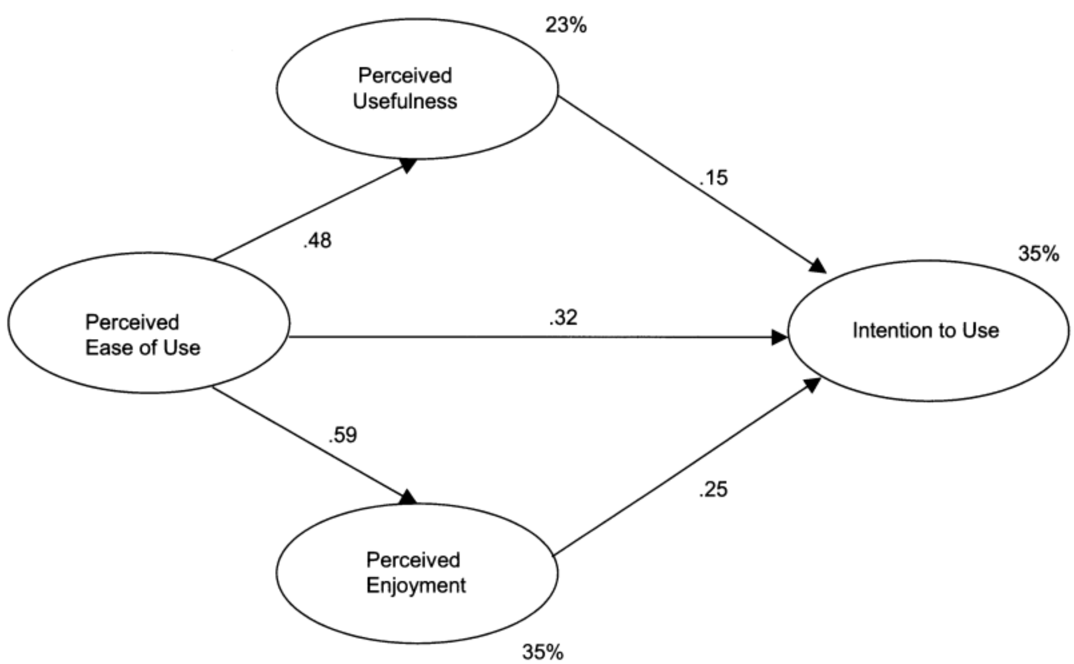

Figure 3.1: Structural equation model for technology acceptance, Van der Heijden, 2004 [14]

3.2 The cognitive theory of multimedia learning

The success of a dashboard is inextricably linked to its features and how they are used in organizations. That said, there is little agreement on exactly what a dashboard looks like and what it should do (Yigitbasioglu, 2012a)[4]. This observation has led to a wide variety of more or less scientifically based techniques and methods for designing useful, enjoyable, and easy-to-use dashboards (Few, 2006; Brath, 2004; Palpanas, 2007)[15][12][3]. Industry has also developed a multitude of tools to support this design process. Among the wide variety of questions that these techniques and methods attempt to answer, the question about the load of a dashboard (the amount of content displayed in the dashboard) seems to us to be particularly attractive. Indeed, dashboards are supposed to avoid information overload, yet they can sometimes include a large variety of information combined with many interactive features, additional material, images, free text and descriptions, ... All in all, this can lead to an overloaded dashboard, which is "too busy" to be used by decision makers. Overload means "receiving too much information". This phenomenon has been observed in various contexts such as communication (too many e-mails, meetings), decision making (too many choices for a consumer in a supermarket), information retrieval and analysis (too many results of an Internet search), etc. (see (Eppler, 2003)[16] for an exhaustive and cross-sectional review of the work on overload). As we saw earlier, dashboards are generally designed to avoid information overload by providing a synthetic view of a large panel of data that can be browsed and analyzed using filters and other exploration mechanisms. By definition, a dashboard should not generate overload. Our theory attempts to deconstruct this idea, drawing a clear distinction between the essential load of a dashboard (the information itself, which can be refined and analyzed by users) and the non-essential load, resulting from visuals, layout, interactive features, etc., which can sometimes reinforce the feeling of overload, rather than diminish it. The previous distinction between essential and non-essential load follows from (Mayer, 2010)[17], where a clear distinction is introduced between different types of cognitive loads:

- Load resulting from essential processing: aimed at making sense of the material (information) presented, including the selection, organization, and integration of words, numbers, and images (filters, pivot, visuals, etc.).

- Incidental processing load: aimed at the non-essential aspects of the material presented (logos,

descriptive text, titles, etc.).
- Representational processing load: aimed at maintaining the verbal or visual representation in working memory (remembering a number to compare it to another number displayed elsewhere in the dashboard).
The specific problem of dashboard overload is not new. Research has already been conducted, for example, on how the colors used in corporate dashboards affect the outcome of the decision-making process (incident processing); the results suggest that excessive use of colors in dashboards creates distraction and increases cognitive load (Bera, 2016)[18], likely reducing the usefulness of the dashboard. To our knowledge, no research has been conducted on the problem of dashboard overload as described above.

3.3 Different approaches of technology acceptance

In order to better understand the technology acceptance model used here, it is interesting to know the different models that have been used to study the acceptance of a technology. Almost 40 years ago a conceptual model was developed to study the adoption of new technologies, based on theories from the field of psychology. The theory of reasoned actions proposes an approach that focuses on the psychology of the user towards technology by incorporating various beliefs and motivations into the model. This model is based on the assumption that individuals are rational decision makers who constantly calculate and evaluate the relevant behavioral beliefs in the context of the action. The attitude referred to in this model is defined by its authors as the set of feelings, both positive and negative, regarding the achievement of the intended behavior. It also refers to the subjective norm. This norm is defined as the user's perception of what the people he/she considers important think about the behavior in question. This model therefore does not only take into account the user's perception but also includes the people around him. The theory of reasoned actions is probably not the most adapted to the present research, but it nevertheless proposes a point of view more focused on the field of psychology which is interesting. The first Technology Acceptance Model appeared a few years later. This model was then extended in many ways involving new factors and variables. The objective of these factors and variables is to explain the central predictors of the TAM as well as possible. In 1985, Davis proposed his conceptual model of technology acceptance.

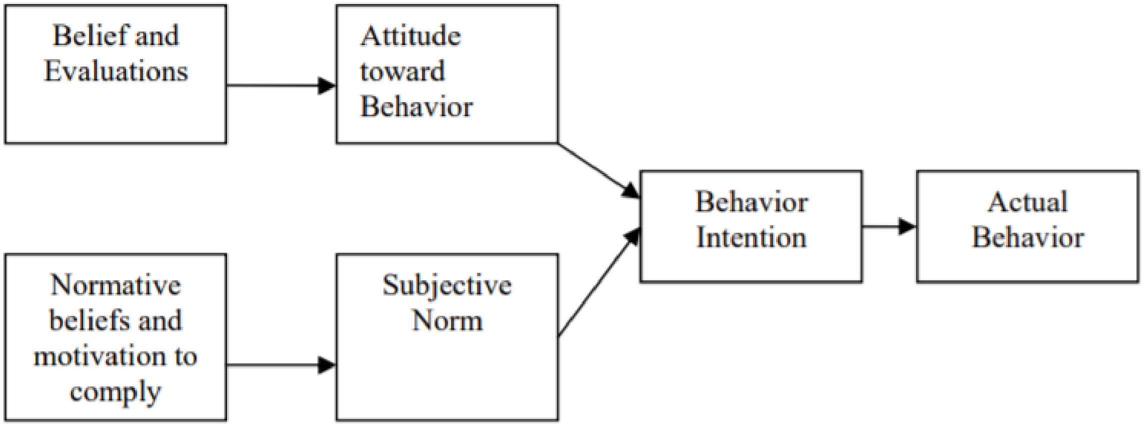

Figure 3.2: The Theory of Reasoned Action (Fishbein and Ajzen, 1975)[19]

He explains in his model that the use of a technology by a user is only a response to a motivation of the user. This motivation is influenced by various external stimuli. These stimuli consist of the characteristics and capabilities of the technology in question. According to Davis, user motivation can be explained by three factors: perceived ease of use, perceived usefulness, and attitude toward use. A key determinant of a user's current use of a technology being his or her attitude toward it, Davis describes its predictors. According to him, perceived ease of use and perceived usefulness influence the user's attitude. He also postulates that perceived ease of use influences perceived usefulness. Davis defined perceived usefulness as the degree to which the individual believes that using the particular system would improve their job performance, while perceived ease of use is defined as the degree to which the individual believes that using the particular system would be effortless.

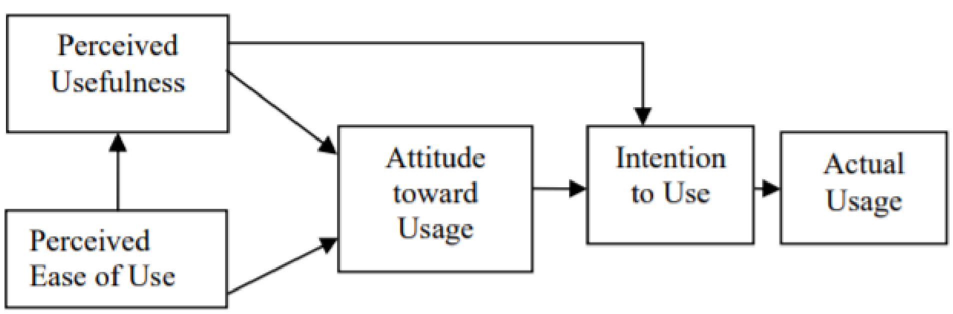

Figure 3.3: The Technology Acceptance Model (TAM) (Davis, 1989)[20]

It was then found that attitude was not a complete mediator of perceived usefulness and perceived ease. This finding led to the development of a new parsimonious model, removing user attitude from the model and including behavioral intention to use as a new variable. This new version originates from the observation that the user can in some cases form a strong intention to use without attitude when the system is perceived as useful. This implies a direct relationship between perceived usefulness and behavioral intention to use in some cases. The removal of attitude from the model also implies the removal of the unexplained direct influence of system characteristics on the attitude variable. Another change from the original TAM was the inclusion of other factors, the external variables, that influence the user's beliefs about the system. The external variables mentioned include the characteristics of the system, the design of the user involvement, and the nature of the process implemented. Davis will later include other variables to improve his model. This will have an impact on the relationships initially formulated. At the same time, other researchers also contributed to Davis' model by proposing various additions. The crucial importance of perceived usefulness on intention to use prompted Venkatesh and Davis to create an extended model, TAM 2, to identify the variables that influence perceived usefulness. These are as follows:

- Subjective norm: the influence of others on the user's decision to use the technology or not.
- Image: the user's desire to maintain a favorable position among others.
- Relevance of use: the degree of applicability of the technology.
- Quality of output: the extent to which the technology has adequately accomplished the required tasks.
- Demonstrability of outcome: the production of tangible results. In addition, experience and voluntariness were included as moderators of the subjective standard.

The TAM can also be used in parallel with other theories. In a 2001 paper, Andrew Dillon looks at the acceptance of information systems [22] . First, he defines acceptance of an information technology as the demonstrable willingness within a group of users to employ an information technology for the tasks it is intended to support. He mentions the recent nature of the research on this subject, a consequence of the more massive use of information systems in many industrial and organizational contexts. He then mentions the five characteristics of an acceptable technology as presented in Rogers' 1995 innovation diffusion theory. These five characteristics are:

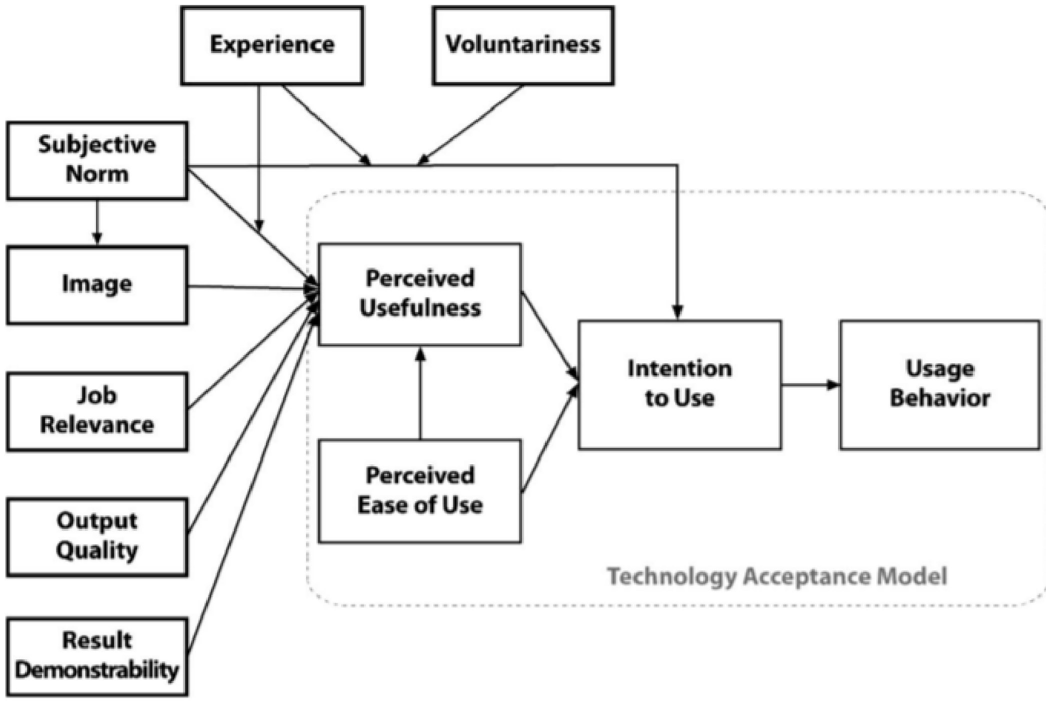

Figure 3.4: The Extended Technology Acceptance Model (TAM2) (Venkatesh and Davis,2000)[21]

- Comparative advantage over other available tools. Here, the comparative advantage of a dashboard lies in the time it saves compared to using raw data. A dashboard will also allow its user to have an overview of the key figures of his company.

- The compatibility of the technology. As far as a dashboard is concerned, it is perfectly compatible with the technologies used in the normal management of a business since it requires only minimal computer equipment.

- The complexity of the technology. This point is central to the research and therefore supports other research on the subject. The term "complexity" used here may refer to the ease of use of the dashboard.

- Testability, or the ability to try the technology before using it. This point is not addressed in this paper. Nevertheless, it underlines the importance for the user to make sure beforehand with the company in question that the dashboard will meet his expectations, failing which he will be able to benefit from a trial period of the technology. Indeed, it is likely that if the final product is far from what was expected, it will negatively impact the user's perceived ease of use.

- Observability, i.e. the visibility of the gains from the use of the technology. It is obvious that the user of a dashboard will only continue to use it if he/she sees the effects in the medium and long term.

In the case of our research, the most important of these five characteristics is the complexity of the technology. Indeed, Dillon notes that the complexity of the technology will play a role in its adoption. We can deduce that an overload of information on the dashboard that would lead to a decrease in its usability could decrease the chances that the dashboard will actually be used.

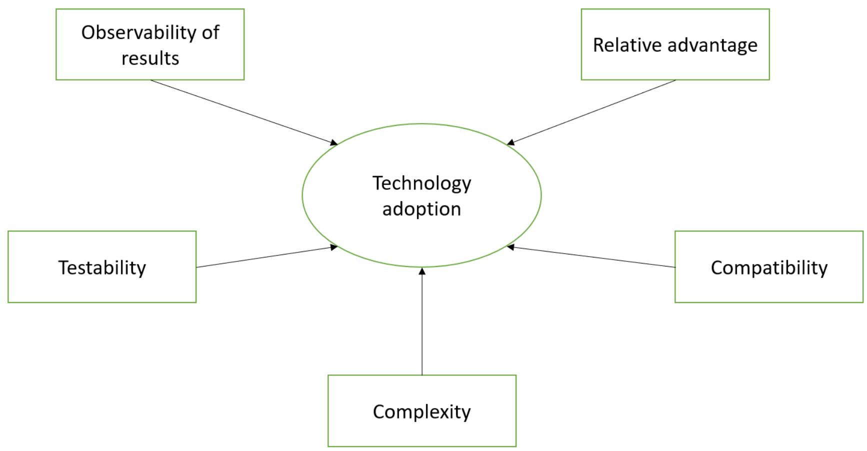

Figure 3.5: Reasons of technology acceptance-Dillon 2001

These different works on technology acceptance allow us to develop the basis of a specific model for the adoption of a BI dashboard. As this paper does not aim to provide a complete review of the literature on the subject, a number of models adapted or specific to certain domains have not been presented.

4 Hypothesis Development

4.1 Hedonic information systems

The more useful the user thinks the dashboard will be, the more likely he is to intend to use the dashboard. If the user feels that by using the dashboard, he or she will be able to make better decisions, be more informed, and/or be informed more quickly, then the user is more likely to want to use the dashboard. Specifically, if a manager wants to know the distribution of sales among different customer segments, and if he thinks the dashboard will help him accomplish his tasks, i.e., answer the question, then he is more likely to want to use the dashboard. This leads to the first hypothesis:

- H1 - Perceived usefulness of the dashboard predicts behavioral intent to use (BIU): the perception of how the dashboard helps the user accomplish their tasks.

If a user thinks the dashboard they have is easy to use, they are more likely to use it. Specifically, if a user thinks that they will not have to make a great mental effort to use the dashboard, then they are more likely to want to use that dashboard. This leads to the following hypothesis:

- H2: Perceived ease of use of the dashboard predicts behavioral intention to use: perceived mental effort required to use the dashboard.

If a user thinks the dashboard he has is enjoyable, he is more likely to use it. If he believes that she will enjoy using the dashboard, then he is more likely to want to use the dashboard. This leads to the following hypothesis:

- H3: Perceived enjoyment of using the dashboard predicts BIU: perceived enjoyment of using a dashboard.

The more the user perceives the dashboard as user-friendly, the more useful he will consider the dashboard to be. Indeed, if the dashboard is easy to use, the user will be more likely to perceive it as useful for performing his tasks. This leads to the following hypothesis:

- H4: The perceived ease of use of the dashboard predicts perceived usefulness.

Finally, the more user-friendly the dashboard is perceived to be, the more pleasant the dashboard will be perceived to be to use. If the dashboard is easy to use, then the user is more likely to enjoy using it. This leads to the following hypothesis:
- H5 - Perceived ease of use of the dashboard predicts perceived enjoyment.
These hypotheses are nothing more than a replication of the hedonic information system theory (HIST), applied to BIS dashboards. We now want to consider the specifics of dashboards and theorize about the causes of perceived ease of use, usefulness, and enjoyment of dashboards. We will therefore turn to the cognitive theory of multimedia learning.

4.2 Cognitive theory of multimedia learning

As mentioned earlier, the specific problem of dashboard overload is not new. Research has already been conducted, for example, on how the colors used in business dashboards affect the outcome of the decision-making process (incident processing); the results suggest that the overuse of colors in dashboards creates distraction and increases cognitive load (Bera2016), likely reducing the usefulness of the dashboard. The preceding description leads us to several additional hypotheses.

First, the essential load concerns the processing of the basic information of the dashboard, i.e., the information that will help the user make the decision, the information about the company. This can be: sales figures, margin, by product, by date, or a gauge showing the upper and lower limits. We consider the essential processing to be directly related to the usefulness of the dashboard; a dashboard with relevant and clear information that can be filtered or further analyzed through filters will help the user make decisions, thus making the dashboard more useful. The representation load of the dashboard represents the processing required for a user to compare information and draw conclusions. The more information and/or interactive features there are (and thus the more essential processing), the higher the representational processing we expect to be. This is because many pieces of information are likely to be discarded in different areas of the dashboard, requiring the information to be stored in memory. This leads to the following hypotheses:
- H6: The essential load of the dashboard predicts the usefulness of a dashboard ;
- H7: The essential load of the dashboard predicts representational processing.

Representational processing refers to the processing of the graph; the energy required to transform the graph image into a usable mental representation. For example, a gauge has a low representational load, while a pivot table or combination chart is more processing intensive. A dashboard where the user has to constantly retain (from memory) a large amount of information will be perceived as less usable. This leads to the following hypothesis:
- H8 - The representational load of the dashboard predicts the perceived ease of use of a dashboard.
Incidental load refers to the treatment of non-essential graphical or textual aspects of elements present in the dashboard. An element is considered non-essential when it can be derived from essential data (e.g., a color code or a KPI displayed in green) or when it is not a useful element for decision making (e.g., a logo or a title). We believe that ancillary processing can sometimes be useful because, even if it does not convey any information about the business, it can help reduce the representational processing of the dashboard, and thus make it easier to use (e.g., color coding). In addition, we believe that a dashboard with some incidental load, such as a logo, slogan, export buttons, etc. will provide some enjoyment to the user. This brings us to the final hypotheses:
- H9 - Dashboard accessory load predicts representational processing;
- H10 - Dashboard incidental load predicts perceived enjoyment of a dashboard.

	Hypothesis	**Origin of the hypothesis**
H1	PU predicts BIU	Technology Acceptance Model
H2	PEU predicts BIU	Technology Acceptance Model
H3	PE predicts BIU	Theory of the hedonic information system
H4	PEU predicts PU	Technology Acceptance Model
H5	PEU predicts PE	Theory of the hedonic information system
H6	EL predicts PU	Cognitive theory of multimedia learning
H7	EL predicts RL	Cognitive theory of multimedia learning
H8	RL predicts PEU	Cognitive theory of multimedia learning
H9	IL predicts RL	Cognitive theory of multimedia learning
H10	IL predicts PE	Cognitive theory of multimedia learning

Figure 4.1: Summary of the hypothesis and their origin

4.3 Definition of the model

By putting all of these assumptions together in the same model, it is possible to create the structural model of the behavioral intent to use. The objective is now to measure the different components of this model in order to determine the strength of the links between these components. If a link is strong enough and significant enough (acceptable p-value), then the corresponding hypothesis can be validated. Otherwise, it will not be validated. Below is a diagram of the structural model.

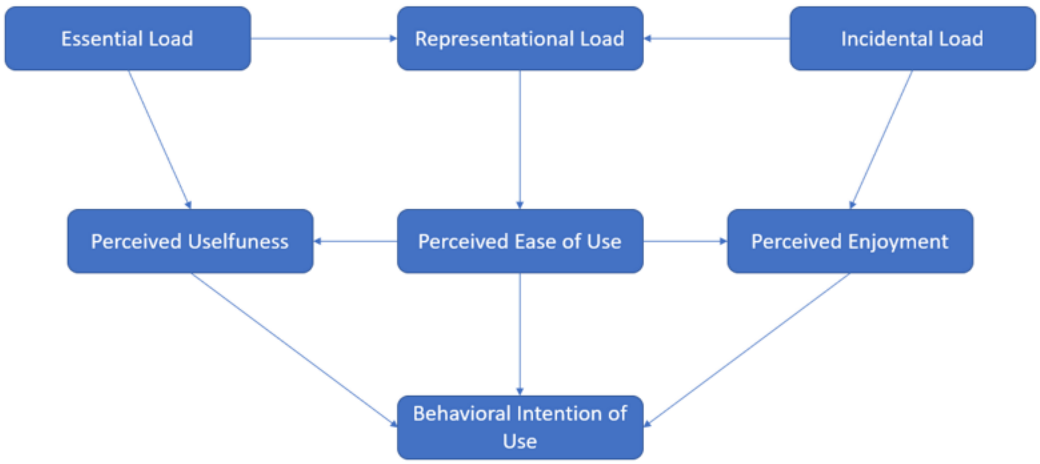

Figure 4.2: Structural model of the behavioral intention of use

5 Research Methodology

The methodology of the research is based first on the design of several BI dashboards with different characteristics. These were developed with the Microsoft "AdventureWorks" database. This database describes the situation of a company selling bicycles and cycling accessories. This data is related to marketing and the dashboard allows the manager to make future decisions about the marketing of the company "Adventure Works". Among these data we can find for example the list of all the products offered with the corresponding sales, the sales data by region or the net income by country and by product category. This data covers a lot of aspects and it is possible to create a large number of tables, graphs and visuals of all kinds that will make sense for the manager. The dashboards have therefore been designed with different characteristics, in terms of number and type of visuals. These dashboards are the core element of the proposed survey. The dashboards are of three types:

- Some lightweight dashboards, with just the minimum amount of information and interactive features.
- Medium dashboards, with some additional information/indicators and functionality.
- Some heavy dashboards, with a lot of text, additional information and indicators, and a wide range of interactive features.

5.1 Data Collection

A questionnaire was then developed for the participants. The first phase of the questionnaire consists of the random assignment of one of the designed dashboards. The participant is asked to become familiar with it, to discover its different functionalities and to "play" with it in order to perceive its qualities and/or defects. Then, a series of questions based on this dashboard are asked to the participant. These questions allow us to estimate the different items that we want to calculate and are based on the theories presented previously. The questionnaire consists of a mixture of a seven-level Likert scale and a seven-point semantic differential. This questionnaire will therefore be linked to the dashboard distributed randomly to the participant, the answers to the latter being influenced by the type of dashboard (light, medium or heavy in terms of information and visuals). The dashboard and questionnaire were tested in a pre-study, involving highly knowledgeable academics in the field who participated in a focus group. This led to improvements in the wording and structure of the questionnaire and the range of dashboards. Next, the pre-study was completed by submitting the questionnaire to a small sample of participants who were invited to provide feedback on the study.

The requirements for participation in this study are

- Be familiar with the concept of a BI dashboard, i.e., not be new to the concept through the study
- Be competent in the field of management or BI. This implies having a management-related role in a company, using BI in one's work, or studying the field of management in graduate school.

Participants were given a clear procedure to follow to complete the questionnaire. First, they were randomly assigned one of the dashboards. Then a case study was presented to give them some context, and an assignment was described to set a clear goal and encourage them to actually use the dashboard. The questions focused on three elements:

- The different loads of the dashboard (essential, representational, and incidental).
- The user's perception of the dashboard's usefulness and perceived ease of use, as well as their perceived enjoyment.
- His/her intention to use the dashboard in the future.

5.2 Measurement

All our variables were measured using multi-item scales. The questions are presented in Appendix A1. Incidental Load is measured by 4 five-item scales (questions 1-4 in Appendix A1). Essential

Load is measured by 4 five-items scale (questions 5-8 in Appendix A1). The Representational Load is measured by 4 five-items scale (questions 9-12 in Appendix A1). Responses to the load questions were among these five propositions: Strongly Disagree; Rather Disagree; Neither Agree nor Disagree; Rather Agree; Strongly Agree.

Perceived usefulness is measured by 4 five-items scale (questions 13-16 in Appendix A1), perceived ease of use by 4-items-scale (questions 18-21 in Appendix A1) and perceived enjoyment by 4-items scale (questions 22-25 in Appendix A1).

The behavioral intention to use was measured by two five-item scales (questions 26-27 in Appendix A1).

5.3 Sample analysis

The collected sample consists of 221 valid instances (suitable for analysis). Here is a brief description of its main characteristics. About 70% of the sample is male, which is probably related to the higher proportion of men in the management field in general. Second, just over half of the participants are between 25 and 50 years old. About a third are 25 years old or younger, which is explained by the relatively high proportion of students or recent graduates who responded to the survey. As far as status is concerned, the majority classes are logically students and employees. Indeed, the easiest people to reach for the survey are business students and employees of business firms. It is more difficult to reach the self-employed, who nevertheless represent 6% of respondents. Finally, it is worth noting that almost a quarter of respondents indicated that they were "looking for work”. This proportion may seem abnormally high but is in fact quite logical given the distribution of the survey. Indeed, the survey was sent to a good number of recent graduates who were looking for their first job in the management field.

Sex	Man	153	69%
	Woman	68	31%
Age	25 years or less	75	34%
	Between 25 and 50 years	116	52%
	50 years or more	30	14%
Status	Student	83	38%
	Employee	73	33%
	In search of a job	52	23%
	Independent	13	6%

Figure 5.1: Description of the sample

6 Results

We used a two-stage SEM procedure proposed by Anderson Gerbing [23] for validation of measures and hypotheses. The first step is a confirmatory factor analysis (CFA) to examine the convergent and discriminant validity of the measurement scales. The second step focuses on hypothesis testing using the structural model. This procedure was performed on a sample of 221 instances.

6.1 Analysis

To analyze the results, we use different statistical tools to determine the quality of the model. Concerning the p-value, it is perfectly acceptable, being 0.000. The root mean square error of approximation shows an acceptable value of 0.047. A value of 0.06 or less being indicative of acceptable model fit. The standardized Root Mean Square Residual (SRMR) is an absolute measure of fit and is defined as the standardized difference between the observed correlation and the predicted correlation. A value less than 0.08 is generally considered a good fit (Hu Bentler, 1999)[24]. The SRLR of this model is therefore acceptable. The Tucker–Lewis index (TLI), analyzes the discrepancy between the chi-squared value of the hypothesized model and the chi-squared value of the null model, and resolves some of the issues of negative bias. The cutoff of this index showing a good fit of the model is 0.95 or more. The value of this model being very close to 0.95, we can still conclude that it is a good fit. The comparative fit index (CFI) analyzes the model fit by examining the discrepancy between the data and the hypothesized model, while adjusting for the issues of sample size inherent in the chi-squared test of model fit, and the normed fit index. A CFI value of 0.95 or higher is presently accepted as an indicator of good fit. Here again, we can consider that it is an indicator of good fit of the model, the value being extremely close to 0.95 These results suggest that the measurement model adequately fits the data.

Concerning the measurement part, we used the procedures proposed by Wong in order to assess

Fit statistics	p-value	CFI	RMSEA	SRMR	TLI
Structural Model	0.000	0.948	0.051	0.047	0.941

Figure 6.1: P-value, Comparative Fit Index, Root Mean Square Error of Approximation,Standardized Root Mean Square Residual and Tucker–Lewis Index of the model

the convergent validity, the reliability and the discriminant validity of our constructs. For this, we compute the different Cronbach's alpha of the constructs, their composite reliability, and their AVE thanks to the construct loadings. For a convergent validity to be considered acceptable, it should have an average variance extracted (AVE) greater than 0.5, as well as construct loadings greater than 0.5, and ideally greater than 0.7. Concerning our 7 constructs, 4 of them have an AVE higher than 0.5 and 2 of them are close to it. On the other hand, the construct "Incident Load" has an AVE of only 0.390 which is generally not acceptable for a convergent validity. For the reliability of our constructs, we use two elements, Cronbach's alpha and composite reliability. For the reliability to be considered acceptable, these two values should be higher than 0.7. We can see in the table that the 7 constructs have indeed Cronbach's alpha and composite reliability all above 0.7. We can therefore conclude that all constructs have an acceptable reliability.

Construct	Cronbach's alpha	Composite Reliability
Essential Load	0,78	0,784
Representational Load	0,77	0,769
Incidental Load	0,73	0,718
Perceived Usefulness	0,80	0,804
Perceived Ease of Use	0,90	0,896
Perceived Enjoyment	0,86	0,862
Behavioral Intention of Use	0,78	0,842

Figure 6.2: Reliability of the different constructs

Then, we perform the assessment of the discriminant validity based on a criterion proposed by Fornell and Larcker [25]. To analyze this criterion, we use the correlation matrix of our 7 constructs, coupled with the square root of the AVE of these constructs. The criterion postulates that to have an acceptable validity discriminant, the square root of the average variance extracted from each construct should be greater than the correlation coefficient of this construct with all the others. In Table 6.4, we have in bold and on the diagonal the square roots of the constructs' AVEs, with the

Construct	Average Variance Extracted (AVE)	Items' loadings
Essential Load	0,477	0,67; 0,71; 0,67; 0,71
Representational Load	0,457	0,74; 0,65; 0,73; 0,57
Incidental Load	0,390	0,59; 0,62; 0,71; 0,57
Perceived Usefulness	0,507	0,78; 0,62; 0,71; 0,73
Perceived Ease of Use	0,685	0,86; 0,88; 0,84; 0,72
Perceived Enjoyment	0,610	0,80; 0,73; 0,82; 0,77
Behavioral Intention of Use	0,641	0,83; 0,77

Figure 6.3: Average variance extracted of the constructs

other values being the constructs' correlation coefficients. We note that the criterion of Fornell and Larcker is not met for all constructs. This is partly due to the low values of the AVE of some constructs, as explained above. We cannot therefore conclude an acceptable validity discriminant for all constructs.

Constructs	EL	RL	IL	PU	PEU	PE	BIU
EL	**0,691**						
RL	0,580	**0,676**					
IL	0,605	0,602	**0,624**				
PU	0,643	0,649	0,573	**0,712**			
PEU	0,568	0,726	0,576	0,707	**0,828**		
PE	0,646	0,661	0,686	0,681	0,662	**0,781**	
BIU	0,636	0,667	0,690	0,723	0,685	0,765	**0,801**

Figure 6.4: Correlation matrix of the constructs

6.2 Structural Model

The first step consists of the variable measurement phase. The essential, representational and accessory loads are measured by 4 questions of the questionnaire. The same applies to perceived usefulness, perceived ease of use and perceived pleasure. The behavioral intention of use is measured with 2 questions. Once each of the variables is calculated, the second step consists of the regression phase. For this we use the hypotheses previously made. The corresponding R-code can be found in Appendix A.2.

Figure 6.2 shows the structural model obtained after the compilation of the R code. The arrows represent the strength of the predictor. Note that as mentioned later, the link between Essential Load and Representational Load and between Perceived Ease of Use and Behavioral Intention of

Use are not significant, so they are not to be taken into account. The previous results did not establish a direct link between perceived ease of use and behavioral intention to use, contrary to what the literature shows for other technologies. It is therefore interesting to examine the reasons for this through different hypotheses.

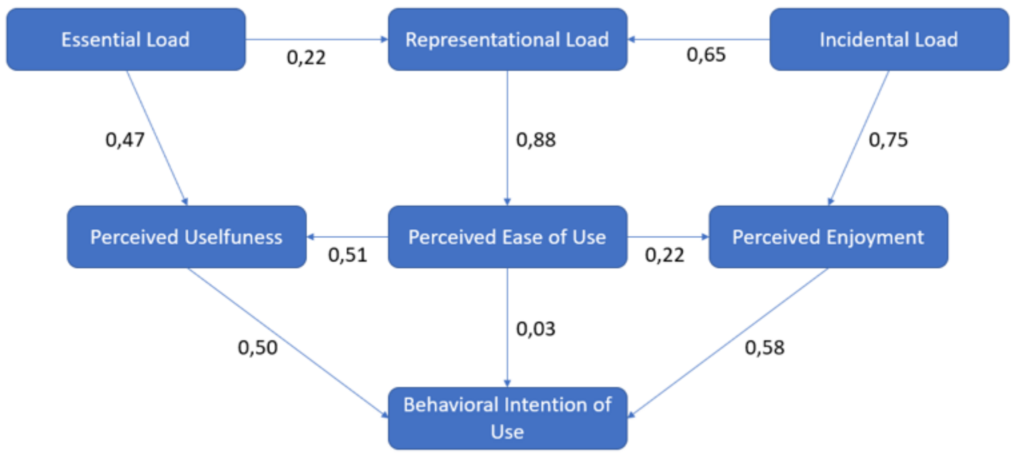

Figure 6.5: Structural model based on the survey responses

6.3 Significance of the results

The p-value associated with the regressions is zero or almost zero everywhere except for two links. The p-value obtained for hypothesis 7 is 0.17 and for hypothesis 2 is 0.76. It is therefore not possible to draw any conclusions for these two hypotheses.The details are given in figure 6.6.

6.4 Hypothesis Validation

- H1 - Perceived usefulness of the dashboard predicts behavioral intent to use (BIU): the perception of how the dashboard helps the user accomplish tasks. This hypothesis was validated by the structural model, with a coefficient of 0.5 on the relationship between perceived usefulness and behavioral intention to use.
- H2: Perceived ease of use of the dashboard predicts behavioral intention to use: perception of the mental effort required to use the dashboard.

Regression	Regression coefficient	P-value associated
Essential Load -> Representational Load	0.22	0.178
Essential Load -> Perceived Usefulness	0.47	0.000
Representational Load -> Perceived Ease of Use	0.88	0.000
Incidental Load -> Representational Load	0.65	0.000
Incidental Load -> Perceived Enjoyment	0.75	0.000
Perceived Usefulness -> Behavioral Intention of Use	0.50	0.000
Perceived Ease of Use -> Perceived Usefulness	0.51	0.000
Perceived Ease of Use -> Perceived Enjoyment	0.22	0.021
Perceived Ease of Use -> Behavioral Intention of Use	0.03	0.764
Perceived Enjoyment -> Behavioral Intention of Use	0.58	0.000

Figure 6.6: Regression coefficients and associated p-values

- H3: Perceived enjoyment of dashboard use predicts BIU: perceived enjoyment of using a dashboard. The analysis of the responses showed a fairly strong relationship between perceived enjoyment and behavioral intention to use. This link was 0.58. Perceived enjoyment is therefore a predictor of behavioral intention to use and the hypothesis is validated.

- H4: Perceived ease of use of the dashboard predicts perceived usefulness. As explained in the validation of Hypothesis 2, perceived ease of use predicts perceived usefulness of the dashboard with a coefficient of 0.51. It is notably due to this relationship that perceived ease of use is a predictor of behavioral intention to use. Hypothesis 4 is therefore validated.

- H5 - Perceived ease of use of the dashboard predicts perceived enjoyment. The same observation applies here in a more measured way since the coefficient is lower, being 0.22. This coefficient is nevertheless significant and we can conclude that the perceived ease of use of the dashboard is a predictor of perceived pleasure, which validates our hypothesis.

- H6: Essential load of the dashboard predicts the usefulness of a dashboard; This hypothesis is validated with a coefficient of 0.47.

- H7: Essential load of the dashboard predicts representational processing. The coefficient for this link is 0.22 but the associated p-value is too high to draw a conclusion from this coefficient. Therefore, the hypothesis cannot be validated.

- H8 - Dashboard representational load predicts the perceived ease of use of a dashboard. This hypothesis is validated, with representational load predicting perceived ease of use with a very good coefficient of 0.88.

- H9 - Dashboard accessory load predicts representational processing. The link between the accessory load and the representational load is quite strong, indeed it is 0.65 as explained previously. This validates the hypothesis.

- H10 - Dashboard incidental load predicts perceived enjoyment of a dashboard. This hypothesis is validated with a coefficient of 0.75.

7 Discussion

7.1 Predictors of the behavioral intention of use

The structural model obtained allows us to affirm the role of predictor of the behavioral intention to use of two constructs: perceived usefulness and perceived pleasure. These two constructs have significant and large coefficients of 0.50 and 0.58 respectively.

7.1.1 Utilitarian system

First of all, concerning the role of predictor of perceived usefulness, this was completely expected by the nature of a BI dashboard. Indeed, it is above all utilitarian because it is used for results. It was therefore logical to obtain a significant coefficient for perceived usefulness.

7.1.2 Hedonic component

Previously, it had been hypothesized that dashboards had a hedonic component due to the different elements used in them. The different means of interaction that make the dashboard 'fun' to use, the accessory elements that aim to make the dashboard more attractive were the basis of this hypothesis. For this reason, the paper on the theory of hedonic information systems was used in the design of the hypotheses. After analysis of the structural model, the results correspond to the hypotheses made in this paper. In particular, the hypothesis specific to hedonic systems, which is that perceived pleasure is a predictor of the behavioral intention to use. The corroboration of the results combined with all the previous research allows us to assert the hedonic character of a dashboard. Nevertheless, this character is not sufficient to conclude that a dashboard is a hedonic system. Indeed, a BI dashboard is by nature a utilitarian system because its objective is to assist its user in making decisions. Moreover, the assumptions of [Van der Heijden, 2004][14], which postulate that perceived ease of use and perceived pleasure are more important predictors of the behavioral intention to use than perceived usefulness, are not fulfilled in this case. The interest of understanding the hedonic character of a dashboard is the creation of several good practices regarding the design of BI dashboards. This allows the designer to take into account more non-essential elements when designing the dashboard in order to improve its use in practice.

7.1.3 Role of perceived ease of use

The previous results did not establish a direct link between perceived ease of use and behavioral intention to use, contrary to what the literature shows for other technologies. It is therefore interesting to examine the reasons for this through different hypotheses. First, what could explain the absence of a direct link between these two items is the fact that respondents are used to more complex IT tools, and that they are little or not impacted by the complexity of dashboards. Indeed, since the respondents are competent in the field of management, this implies that most of them are used to using various management tools, which can sometimes be much more complex than those proposed by the dashboards in the study. Although the most complex dashboards proposed to respondents are significantly less user-friendly than the lightest ones, they are still quite affordable for someone used to computerized decision support tools. Second, another hypothesis is that the type of study had an impact on this item. As will be explained in the "Limitations" section, the fact that respondents only used the dashboard for a few minutes may have underestimated the importance of ease of use in the medium to long term.

7.2 Influence of the different loads

The structural model also highlights the different importance of the types of dashboard load. Nevertheless, it is important to note that the constructs of the different loads present convergent validities and discriminant validities much more questionable than the other constructs. The analysis of these results must therefore be taken with some distance from this.

As for essential load, we were unable to conclude that it was a predictor of representational load because, although it had a coefficient of 0.22, the associated p-value was too high (0.178). On the other hand, the coefficient concerning its relationship with perceived usefulness is significant and high (0.47). The conclusion of this is that the essential load is indeed a predictor of perceived utility. The load relative to the pure information of the dashboard is thus a good predictor of the utility that the user of the dashboard will perceive.

The representational load was found to be a very good predictor of perceived ease of use, with a large associated coefficient (0.88). The load to maintain the verbal or visual representation in working memory is therefore crucial for the user to perceive the dashboard as easy to use.

Concerning the incidental load, the load concerning the non-essential aspects of the dashboard, proved to be a very good predictor of the two constructs to which the research hypotheses had associated it. First, it is a significant predictor of representational load. Second, it is a strong predictor of perceived pleasure. These results therefore highlight the importance of incorporating various non-essential elements in a BI system in order to create a certain pleasure of use in the user, which in turn will impact his behavioral intention of use.

7.3 Practical implications

Based on the results of this study, it is possible to establish a few recommendations for BI dashboard designers. These recommendations aim to optimize the use of the dashboard by the use and thus respond to the client as well as possible.

Firstly, pure information does not represent the totality of the added value of a dashboard and one should therefore not focus solely on it when designing the dashboard. The importance of the perceived pleasure caused by the presence of incidental load has been demonstrated in this paper and this incidental load should be present enough in the dashboard for the user to find satisfaction in using it. It is important to keep in mind that in a competitive field such as BI consulting and with the many software packages that allow for relatively simple dashboarding, the user potentially has a wide range of choices for their BI system. Of these choices, the majority may present the essential information that will constitute the usefulness of the dashboard but some of these may not focus enough on the hedonic component of these dashboards. The risk of this is that the user prefers, for the same utility, the dashboard that gives him the most satisfaction in use.

Second, and unlike many other technologies, ease of use was not a direct predictor of behavioral intention to use. The hypothesis was made above that this is probably related to the skills of managers using dashboards, which would be sufficient to prevent a complex dashboard from directly affecting their intention to use. The associated recommendation would therefore be not to put this ease of use ahead of the other predictors, namely perceived usefulness and perceived pleasure. This implies that representational load should not be established at the expense of essential and incidental load.

As these recommendations are based on the results obtained in this study, it is obvious that they could be modified if other studies, presenting better quality responses, were to present final results different from those obtained in this paper.

7.4 Research Tracks

7.4.1 Optimal load

After having defined the different factors that predict the behavioral intention of using a dashboard as well as the impact of a dashboard overload on the actual use, the next logical step would be to try to determine the optimal load of a BI dashboard. This is not the objective of this paper, but it is possible to propose avenues to explore in order to optimize BI dashboards. One avenue to explore would be to propose to a qualified audience a questionnaire similar to the one proposed here, focusing on the behavioral intent of use. The difference here would be that the proposed dashboards would only vary in the number of items. This would make it possible to determine the load at which a user will on average use a dashboard the most. This load should, of course, be divided into essential load, representational load, and incidental load when analyzing the responses, with a view to determining differences in usage when these types of loads change. Another approach, which is probably more complex to implement, would be to ask respondents to create the dashboard they consider ideal using different visuals. It would then be possible to calculate the number of elements selected on average, as well as their types. This would require highly qualified respondents, such as BI consultants, who are used to developing such systems and are familiar with customer feedback on dashboards and their use. These leads could be the subject of further research into the optimal load of a dashboard or the impact of information overload on the use of a BI dashboard.

7.4.2 Different adaptation of the TAM to the adoption of dashboards

In this paper, we used a version of the TAM that includes perceived usefulness and perceived ease as predictors of behavioral intention to use. To this we added a third construct predicting intention, perceived enjoyment. The predictors of these constructs are the different loads of the dashboard. This model is well suited for a first study specific to BI dashboard adoption because of its simplicity and efficiency. Nevertheless, based on the literature mentioned in section 3, it would be possible to build a more comprehensive model, including more explanatory variables of the different predictors of usage intention. This model would involve extensive research on the different variables to be taken into account and would require precise specification of these in the survey design.
The objective here is not to describe what such a model would look like, as this would be too speculative, but some hints can be found in the different models presented in section 3. For a more complete review of the different models of technology acceptance, it is possible to refer to 'A Critical Review of Technology Acceptance Literature' (Li, 2010)[26] or 'Technology acceptance model: a literature review from 1986 to 2013' (Nikola Marangunic´, Andrina Granic, 2014) [27].

7.5 Limitations

The purpose of this section is to highlight the limitations of our study, particularly with respect to the methodology employed. First, it is important to note that respondents to the survey on which our results are based used the dashboard for a short period of time, just what is necessary to understand how it works and to become familiar with the tool. This may have implications for their perception of the tool. For example, perceived enjoyment may have been overestimated by respondents because they did not analyze the dashboard from a 'long-term' perspective and decided to give more importance to the enjoyment they perceived during use. Ease of use may have been undervalued, as respondents were not particularly affected by this element, knowing that they would never use the dashboard again after the survey. It is therefore important to take a step back from the way the responses were collected, and keep in mind that the results could vary if the same experiment was conducted over a longer period of time. This scenario would obviously be preferable but was not possible here for obvious cost reasons.

Secondly, the sample on which the results are based could be criticized to some extent. Indeed, although a prerequisite for participation in the survey is that the participant has management skills, the skills of some participants may be quite limited. Indeed, some of the respondents are graduate students, and although they have a good theoretical basis in the field of management, the majority of them do not yet have experience in BI-assisted management. It is difficult to say whether gaining experience would change their perception of dashboards much, but the results might vary a little if the panel of respondents consisted only of managers or management experts.

Finally, another major limitation of this paper is the "discriminant analysis" part of the constructs. This one did not prove to be ideal according to the criterion we used. Indeed, it revealed unexpected correlations between some constructs. These correlations did not correspond to the research hypotheses. This can be explained by low quality answers, or by a bad specification of some constructs. It would also be interesting to see if these correlations persist with a larger and more appropriate sample.

8 Conclusion

Both research questions were addressed and the majority of the hypotheses made in Section 4 were validated. The adaptation of the TAM model to BI dashboard adoption revealed the crucial importance of perceived usefulness, as expected for a utilitarian system, but also showed the importance of perceived enjoyment, which is often a strong predictor of hedonic systems. As for perceived ease of use, although it was not possible to conclude that it was a predictor of behavioral intention to use, it was shown to have a role as a predictor of perceived usefulness and perceived pleasure. The hedonic nature of a BI dashboard was then discussed and validated in the results analysis discussions. The importance of the different loadings of a BI dashboard were also discussed, especially the incidental loading, which was found to be a strong predictor of perceived enjoyment. This demonstrates the importance of this load in BI dashboard design. Concerning the influence of information overload on the behavioral intention of use and the optimal load that a BI dashboard should have, tracks are given to study it in depth, the objective of this paper not being the analysis of information overload in a specific way but the study of the adoption criteria of BI dashboards in a general way. Nevertheless, as the information overload is one of the adoption criteria of a decision support system, it could be interesting to study it in order to determine the optimal load of a BI dashboard and thus help the designers to propose the most adapted services to their customers.

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A Appendix

A.1 Survey questions about the dashboard

1. The dashboard contains a reasonable number of images, logos, arrows and other static visual elements.
2. The dashboard contains a reasonable amount of headlines, text, and other notations
3. The dashboard has appropriate use of color and a good balance of 2D/3D visuals
4. The dashboard contains a reasonable number of buttons, external links, and interactive objects.
5. The dashboard breaks down product information into a sufficient number of analysis axes
6. The dashboard displays an adequate amount of indicators (metrics or numbers) with enough detail about AdventureWorks products.
7. The dashboard sufficiently highlights trends, cycles, or other patterns in the AdventureWorks product data.
8. The dashboard provides appropriate interactions with product information.
9. The dashboard makes all product information easily accessible.
10. The dashboard makes it easy to compare and relate information about different products.
11. The dashboard is clearly organized and not too scattered.
12. The dashboard displays a reasonable amount of information that I could easily remember.
13. The dashboard helps me decide more quickly and easily about the business qualities of a product.
14. The dashboard is better than interviews or verbal discussions for deciding which product to recommend to AdventureWorks.
15. After reading the dashboard, I feel more informed about AdventureWorks products.
16. The dashboard is important to me in order to give advice to AdventureWorks.
17. What is the number of the dashboard that was assigned to you in Part 2 of the survey?
18. The interaction with the dashboard is clear and understandable

19. The dashboard is easy to use and I can find information easily.

20. I find it easy to pull the information I need from the dashboard.

21. I would share the dashboard even with someone who is not computer literate.

22. I find the dashboard [Sloppy, Neat].

23. I find the dashboard [Boring, Fun].

24. I find the dashboard [Unpleasant, Pleasant].

25. I find the dashboard [Hollow, Interesting]

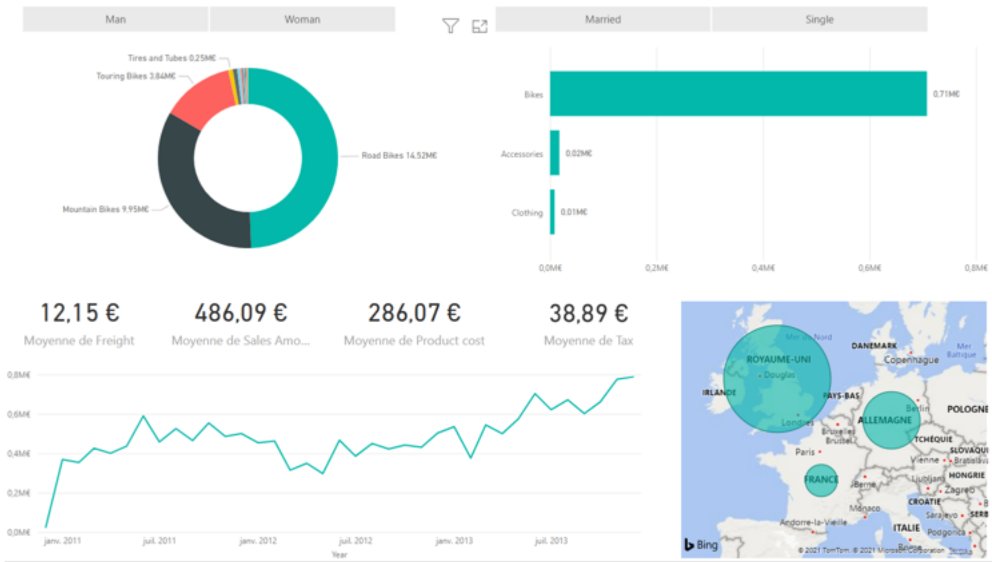
26. In the near future, I predict that I will use the dashboard again to carry out my consulting assignment with AdventureWorks.

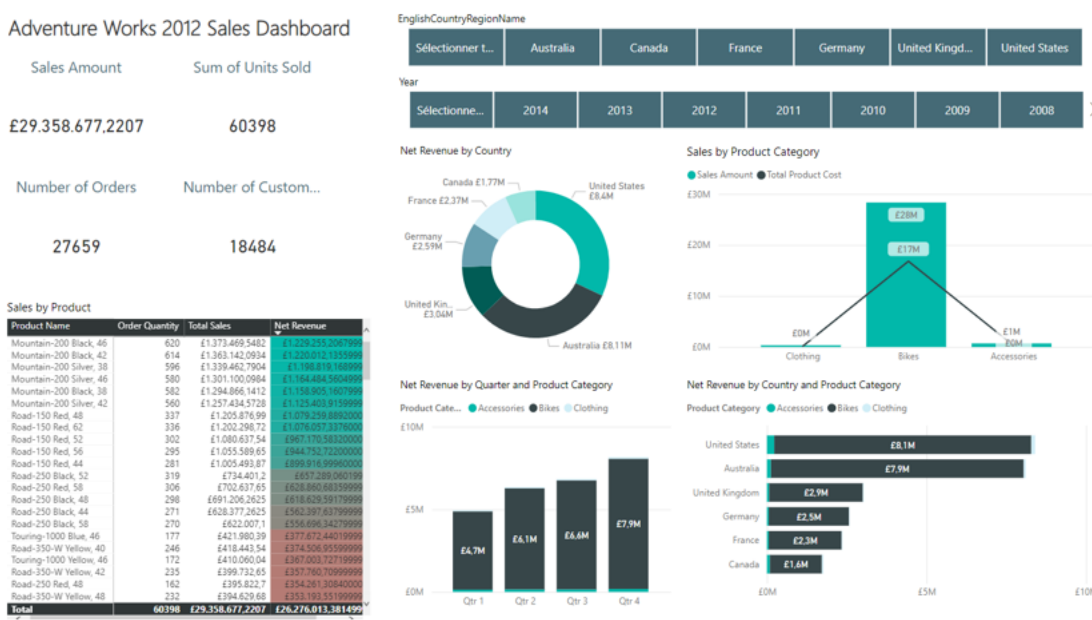
27. If hired by Adventure Works, I would continue to work with the current dashboard and would not request another dashboard.

A.2 R-code used for the structural model

```r
model6 <- '
#measurement
el=~EL1+EL2+EL3+EL4
rl=~RL1+RL2+RL3+RL4
il=~IL1+IL2+IL3+IL4
pu=~PU1+PU2+PU3+PU4
peu=~PEU1+PEU2+PEU3+PEU4
pe=~PE1+PE2+PE3+PE4
biu=~BIU1+BIU2
#regressions
rl~el+il
pu~el+peu
peu~rl
pe~il+peu
biu~pu+peu+pe
'
fit6<-cfa(model6,data=Data)
summary(fit6,fit.measures=TRUE, standardized=TRUE)
fitMeasures(fit6, c("cfi","rmsea","srmr"))
semPlot::semPaths(fit6,what='paths', whatLabels='stand',rotation=1)
```

A.3 Examples of dashboard proposed for the survey





A.4 Table of abbreviations

Abbreviation	Signification
EL	Essential Load
RL	Representational Load
IL	Incidental Load
PU	Perceived Usefulness
PEU	Perceived Ease of Use
PE	Perceived Enjoyment
BIU	Behavioral Intention of Use
TAM	Technology Acceptance Model