Abstract

The rise of Twitter and its explosive growth over the past few years come with the question of what underlying factors are responsible for this increase in the usage and acceptance of this Web 2.0 application. In this research, the Unified Theory of Acceptance and Use of Technology (UTAUT) is used to investigate the success factors of the Twitter. Firstly, a literature review is provided to build a knowledge base and overview of the technology acceptance models that have built up the UTAUT model. An online survey was carried out and with 109 subjects, an analysis was conducted on the gathered data. Using the Product-Moment correlation coefficients and linear regression, results show that Performance Expectancy is the biggest contributor to the intention to use Twitter. Effort Expectancy and Social Influence were shown have a significant crude effect on Behavioral Intention, but the significance disappears when the research model was investigated as a whole with multiple linear regression. Facilitating Conditions showed to have a significant relationship with the use of Twitter in the context of sharing information. Gender was shown to moderate the relationships between Performance Expectancy, Effort Expectancy, Social Influence and Behavioral Intention. Age did not have this moderating effect, as was assumed by the original UTAUT model. Experience was shown to have a direct significant relationship with Behavioral Intention.

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1 Introduction

We can hardly think of a world without information technology (IT) anymore these days. In business environments as well as in households, computers have become a part of our daily lives. With the rise of the internet (in the Netherlands, according to the Central Bureau for Statistics (statline.cbs.nl) in 2004 already 73 percent of the people had access to the internet at home) IT became an even bigger part of our daily lives.

As the internet is becoming more and more a part of our daily lives, the internet itself seems to be developing as well. With upcoming technologies such as those incorporated in the conceptual framework of Web 2.0, applications evolve whereby users are more involved in the process of adding, removing and editing online content (Kim, Yue et al. 2009). Examples of these kind of applications are Social networks (such as Facebook, MySpace and Hyves), Blogging sites (Twitter, blogger.com) and Virtual media sharing platforms such as Youtube and Flickr.

This type of involvement is typical for Web 2.0 applications and has been called 'Collaboration' or 'Participation' in previous research. One example of these Web 2.0 applications that gained popularity in an explosive tempo recently, is the micro-blogging site Twitter. Twitter is a micro-content Online Social Network (OSN) that is able to process Short Message Service (SMS) data over multiple delivery channels (Krishnamurthy, Gill et al. 2008). Users of Twitter can thus share short messages with their followers on what their current activities are. Thereby they can use cell phones, other social networks or the interface of Twitter online to share this information.

From February 2008 till February 2009 the growth rate of Twitter in the US was 1382% (McCarthy 2009) to a total of 7,038,000 members. In comparison, Facebook had in the same year a growth rate of 228% to a total of 65,704,000 members. These figures show that Twitter has an immense popularity currently and the success of this service rises the questions of how and why such an application can grow that fast.

Previous research has pointed out the success factors of web sites in the field of e-commerce, or Business-to-consumer web sites (Ranganathan, Ganapathy 2002, Liu, Arnett 2000). Also, another stream of research exists specifically on the acceptance of (internet) technologies, whereby the Technology Acceptance Model (whether or not adjusted) is seemingly the most frequently used research tool (Lederer, Maupin et al. 2000, Gefen, Karahanna et al. 2003). Besides the Technology Acceptance Model (TAM), several other models and theories have been developed during the last few decades on the topic of Individual acceptance. In a research of (Venkatesh, Morris et al. 2003), the

Unified Theory of Acceptance and Use of Technology (UTAUT) has been proposed and validated. This model integrates eight different acceptance models into one unified model. Our research endeavors to adapt the UTAUT model for Web 2.0 technologies in order to find the success factors for Twitter.

The aforementioned increase in collaboration and participation of users on the internet combined with other possibilities that come with Web 2.0 applications, rises a question on how this increase in functionality on the internet influences the way new (internet) technologies and applications get accepted by users. In this research we will explore the new possibilities of Web 2.0 applications, redefine the UTAUT research model into a model that takes into account these new possibilities, and empirically validate the newly proposed research model by a survey amongst users of the Web 2.0 facility Twitter.

1.1 Relevance of this research

Our literature review showed that there is scientific gap in the literature on the acceptance of Web 2.0 technology applications in particular. Also, many of the discussed technology acceptance models in have been used many times in previous research (Venkatesh, Morris et al. 2003). The UTAUT model is relatively new (the Technology Acceptance Model for example is from 1989) and can still be enhanced to gain explanatory power in specific situations. We endeavor to use the UTAUT model for Web 2.0 applications and validate this research model in a new environment.

With knowing what drivers cause users of new technologies to accept these technologies, we can begin to understand how we can design these new applications in such a way that new users will more likely adopt these new technologies. In the case of Web 2.0 applications, it seems to be useful to understand as well how adopters of other Web 2.0 applications adopt new Web 2.0 applications, especially in comparison to users that are completely new to Web 2.0 technologies. With Web 2.0 technologies being used in educational, social, research and business settings (Kim, Yue et al. 2009), we can by understanding the acceptance of these technologies begin to work towards applications on the internet that are even more useful and accepted than they are now.

1.2 Motivation

With a severe interest in psychology and information systems, this research has evolved out of a selection process that went from studying the unconscious mind of human beings to the latest Web 2.0 technologies.

1.3 Scope of the research

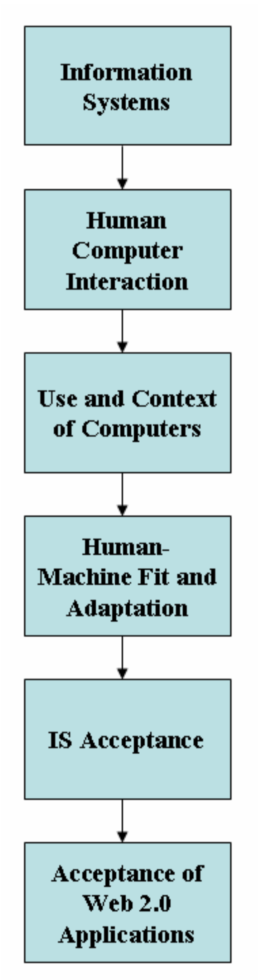


Figure 1; Break down of our scope

In the stream of research that governs Information Systems, we focus on the field of Human-Computer Interaction (HCI). This field of research has been broken down by (Perlman 2009) into six different sections. In section 2.1 we will go further into this breakdown. When we look into these fields, this research falls into the category of 'Use and Context of Computers'. This field has been divided again into three different areas, of which this research is in the field of 'Human-Machine Fit and Adaptation'. We take it even one step further, by defining that this research is on the stream of technology *acceptance.* Here we primarily focus on the initial adoption, where we implicitly assume that intention is a main driver of IS usage. Some recent research has been published on systems *continuance,* which is beyond the scope of this research. In IS continuance other factors, such as habit play a significant moderating role in the relation between intentions and the continuance of IS usage (Limayem, Hirt et al. 2007). Figure 1 is a visualization of the breakdown of the scope of our research.

1.4 Research question

Broadly, in this research we will address the following research question:

What are the success factors behind the success in acceptance of the Web 2.0 application Twitter?

More specifically we will in order to answer this research question, we will:

- Introduce the field of Human-Computer Interaction and investigate more deeply the field of Technology Acceptance with its research models and methods to provide a basis of understanding for this research. We will thereby provide an overview of prior research in these fields that is relevant for this study.
- Investigate prior research literature on Web 2.0 technologies and the micro-blogging service Twitter and provide an overview of these technologies.
- Formulate hypotheses based on the conclusions from the aforementioned literature study.
- Integrate the implications of Twitter into a research model from the field of Technology Acceptance and empirically test this model in this new environment.

2 Literature Review

2.1 Introduction

This section contains a review on the literature that functions as a foundation on which we build our research. In this section we use a top-down approach to discuss the fields of research that are of importance for our own research. We start with an introduction to Human-Computer Interaction, followed by a section on Information Systems acceptance. In this last section we discuss several models that have been used widely in past research. We discuss the models that have formed the Unified Theory of Acceptance and Use of Technology (UTAUT) briefly and the UTAUT itself more in-depth. After the section on IS Acceptance follows an introduction on Web 2.0, where we discuss some Web 2.0 applications briefly and the application we base our research on (Twitter) more in-depth. We end this chapter with some conclusions on the literature review and from there we formulate the hypotheses for our research.

2.1.1 Literature search method

The literature we use in this review comes from several sources. One source we have used as a starting point frequently is the Association for Information Systems (or AIS, available from http://www.aisnet.org). With search terms like 'UTAUT', 'micro-blogging', 'Twitter', 'Technology acceptance' and so forth we have searched through the e-library of this website. Papers that have been used for this literature review had their references and bibliographies; we used them as well to find literature that supports our research. In cases these references were hard to find on the website of AIS we searched with a search engine on the internet named 'Google Scholar' (available from scholar.google.com). Here were often links to the library of Erasmus University so in that way we had access to those documents.

2.2 An introduction to Human-Computer Interaction

The field of Human-Computer Interaction is concerned with the way people use and work with technology (Jacko, Sears 2003). With studying how humans and computers interact with one another, this field has the objective of providing methods and recommendations on how to ensure that emerging technologies add maximum value to the user(s) of this new technology. Terms like quality, ease of use, usefulness, satisfaction, and safety are thereby measures to provide these methods and recommendations.

In the early 1960's, just before the end of the era of small independent machines, programmers were already dealing with how to make their computer printouts readable and understandable for their users, amongst other human factor issues (Pew 2003). This is is just one illustration that ever since there was interaction between humans and computers, issues regarding the human factors have existed. When in the 90's the internet became more available to households, studies on how to increase web usability evolved accordingly within the field of HCI. With the ever changing and evolving technologies (Global Positioning Systems (GPS), Personal Digital Assistants (PDA's), Mobile phone technology, Bluetooth, RFID to name a few), the field of HCI is changing as well to get a better understanding of information technology from the end-user's point of view (Lozano, Gallud 2008).

As the range of technologies and studies in HCI cover many topics, we will begin with breaking down the field of HCI into smaller chunks. HCI is broken down into six fields of research at this point in time (Perlman 2009):

- **N** The Nature of HCI
  - N1 (Meta-)Models of HCI
- **U** Use and Context of Computers
  - U1 Human Social Organization and Work
  - U2 Application Areas
  - U3 Human-Machine Fit and Adaptation
- **H** Human Characteristics
  - H1 Human Information Processing
  - H2 Language, Communication, Interaction
  - H3 Ergonomics
- **C** Computer System and Interface Architecture
  - C1 Input and Output Devices
  - C2 Dialogue Techniques
  - C3 Dialogue Genre
  - C4 Computer Graphics
  - C5 Dialogue Architecture
- **D** Development Process
  - D1 Design Approaches
  - D2 Implementation Techniques
  - D3 Evaluation Techniques
  - D4 Example Systems and Case Studies
- **P** Project Presentations and Examinations

As stated in Section 1.2, this research falls within U3, 'Human-Machine Fit and Adaptation', which in turn falls into the category 'Use and Context'. In the next section we will take these steps to form the scope of our research (see also Figure 1).

2.3 Individual user acceptance of Information Technology

Since mid 1970's individual use of Information Technology and the factors that influence the use have been a subject of importance in Management Information Systems Research. This stream of research began when organizations and researchers discovered that adoption of new technology was not living up to expectations (Compeau, Higgins 1995). Prior research involves studies in which models have been designed with which one can measure acceptance of information technology; (Fishbein, Ajzen 1975)'Theory of Reasoned Action was one of the first models that gained widespread acceptance. Their model inspired many other researchers for the development of other Technology Acceptance models.

Being able to predict usage of new technology accurately, allows one to assess whether implementations of such a technology would be worthwhile. Information technology that is not used or will not be used simply cannot improve organizational performance. The stream of research that uses intention as a predictor of behavior to establish an understanding of the usage of information technologies will be the foremost inspiration for the current research. This method lends itself particularly well for IS research (Venkatesh, Morris et al. 2003) and therefore will be the focus of this research.

Figure 2 illustrates the basic concept for User Acceptance Models with Intention as predictor. Here we see that the actual use of IT is the dependent variable and the determinants are the intentions to use IT and the individual reactions to using IT. The latter also have a direct impact on the intentions to use IT and the actual use generates individual reactions, making the loop complete.

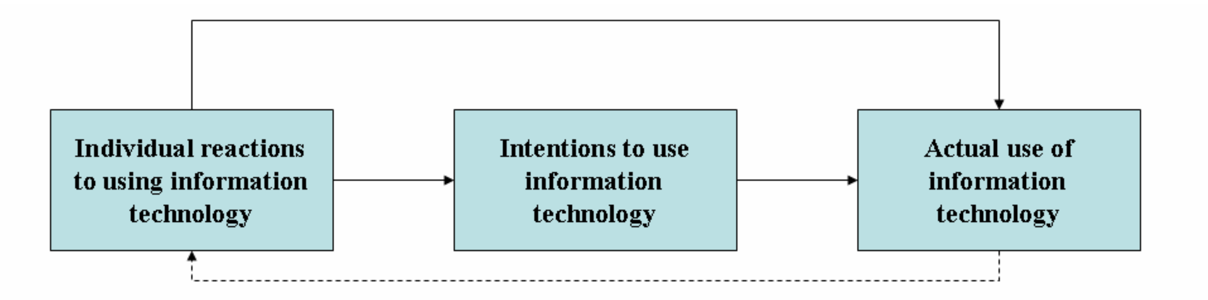


Figure 2; Basic Concept Underlying User Acceptance Models with Intention as predictor

In the next few sections we will provide an overview of the prior research models in the field of Technology Acceptance. The Technology Acceptance Model, derived from the Theory of Reasoned Action, seems to be a largely used model to predict the usage behaviour of information systems. Also before we describe UTAUT, the research model that we will use for this research, we will describe the Diffusion of Innovations model of Rogers and the Social Cognitive Theory of Bandura. Then we will describe the Theory of Planned Behavior and the Model of PC Utilization.

2.3.1 Theory of Reasoned Action (TRA)

(Davis, Bagozzi et al. 1989) were one of the first that applied a theory from social psychology on human behavior on the individual acceptance of information technology. They applied the Theory of Reasoned Action (TRA) from (Ajzen, Fishbein 1980) which explains the relation between beliefs, attitudes and intentions and thereby explaining the generation of behaviors. Figure 3 shows the factors and the according relationships between these factors, and below figure 3 we explain the model backwards, starting by the Actual Behavior.

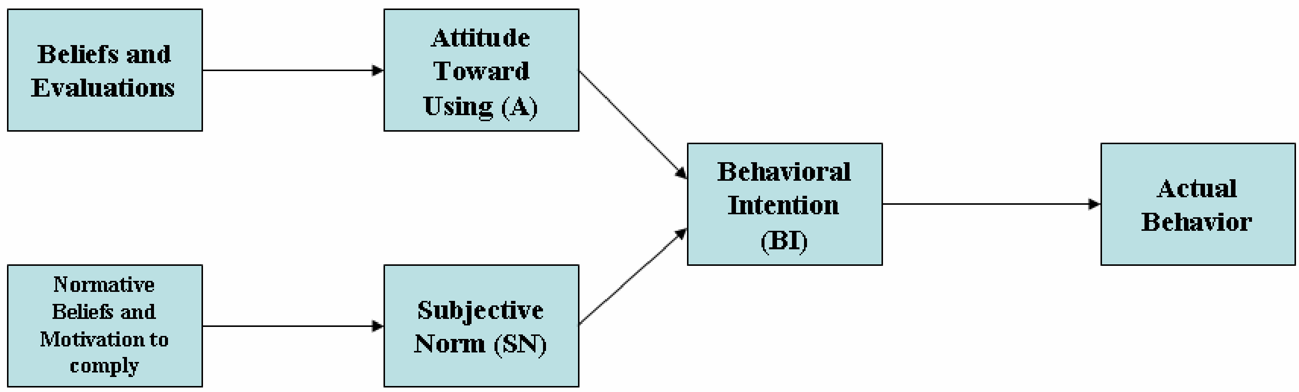


Figure 3; Theory of Reasoned Action (TRA)

TRA explains how Actual Behavior is being preceded by other factors. The model shows that Actual Behavoir is driven by the person's Behavioral Intention (BI) (Fishbein, Ajzen 1975). This behavioral intention is driven jointly the person's Subjective Norm (SN) and his or her Attitude (A). Subjective Norm here refers to "the person's perception that most people who are important to him think he should or should not perform the behavior in question" (Fishbein, Ajzen 1975). Attitude (A) is defined as "the individual's positive or negative feelings about performing the Actual Behavior." These factors on their turn are determined by the factors 'Normative Beliefs and Motivation to comply' and 'Beliefs and Evaluations', respectively. The factor 'Beliefs and Evaluations' is defined as "the person's beliefs about the consequences of the Actual Behavior, multiplied by the Evaluations of those consequences." In other words, the Attitude towards a certain behavior is determined by the way a person thinks this behavior will have an impact, also taking into consideration how important the person perceives this impact is for him. The factor that determines SN is defined in a similar way; "the Normative Beliefs (what the person beliefs his or her most important people think about the performance of the Actual Behavior) multiplied by the motivation to comply with this." So we could understand this factor as the way the person's important surrounding people have their Beliefs and Evaluations, also taking into account the level of willingness to adjust the person's behavior to those peoples' Beliefs and Evaluations. TRA is a general but fundamental model upon which other acceptance models have been built, as we can see with the Technology Acceptance Model.

2.3.2 Technology Acceptance Model (TAM)

By adapting the TRA (Fishbein, Ajzen 1975), the Technology Acceptance Model (TAM) was created in order to model user acceptance for information systems specifically (Davis, Bagozzi et al. 1989, Davis 1989). As Figure 4 displays, TAM theorizes that the Attitude toward using a system (A) is determined by two factors; Perceived Usefulness (U), defined by "the extent to which the user beliefs that use of the system will enhance his or her job performance in an organizational context", and Perceived Ease of Use (EOU). The latter is defined as "the extent to which use of the system will be free of effort" (Davis, Bagozzi et al. 1989). External variables such as system characteristics and the skills of the user will have a moderating effect on U and EOU and the easier the user perceives the system to be in use, the more useful it can be; hence the relation between EOU and U. The behavioral intention to use the system is determined by A and U. The direct relationship between BI and U is based on the belief that people within an organizational setting will form intentions toward the use of a system when they perceive the system might increase the job performance. This increase in job performance might, regardless the positive or negative feelings that come with the use of the system, bring the user various rewards such as pay increases or job promotions (Davis, Bagozzi et al. 1989).

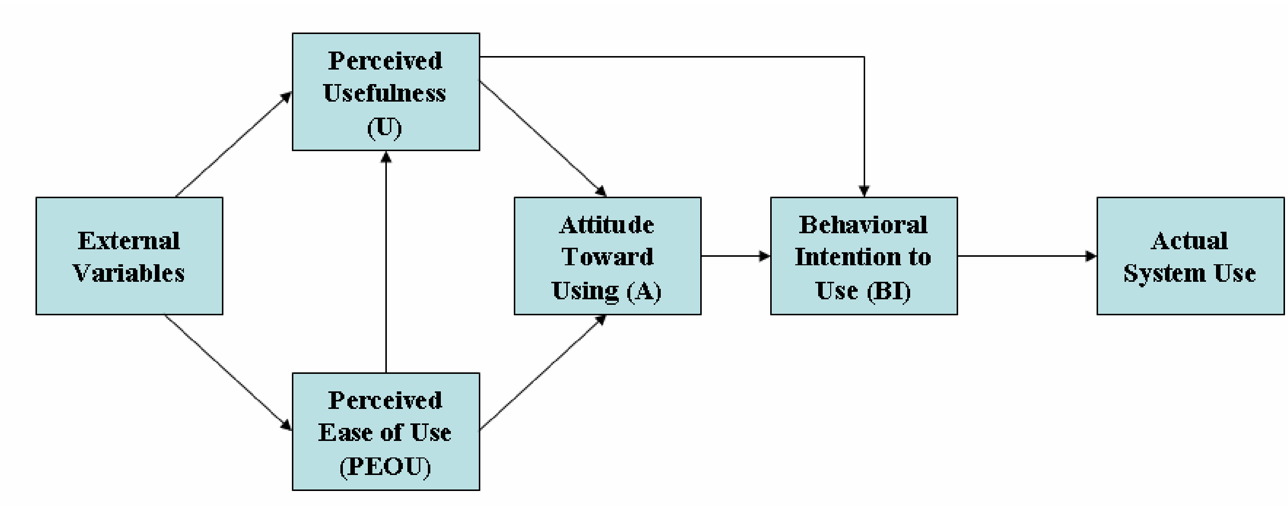


Figure 4; Technology Acceptance Model (TAM)

In addition to TAM, (Venkatesh, Davis 2000) have extended TAM and called their model TAM2. They added Social Influence Processes (Subjective Norm, Voluntariness and Image) and Cognitive Instrumental Processes (Job relevance, Output Quality, Result Demonstrability and Perceived Ease of

Use). They also pointed out that for mandatory systems, the systems that are not used voluntarily; Subjective Norm has a bigger effect on Usage Intentions than EOU and U.

2.3.3 Motivational Model

Another model that seeks to explain intention to perform a certain behavior is the Motivational Model. Introduced by (Davis 1992), the Motivational model consists of three constructs; Extrinsic Motivation (EM), Intrinsic Motivation (IM) and Behavioral Intention to Use (BI). Both Intrinsic Motivation and Extrinsic Motivation have an effect on the Behavioral Intention to Use.

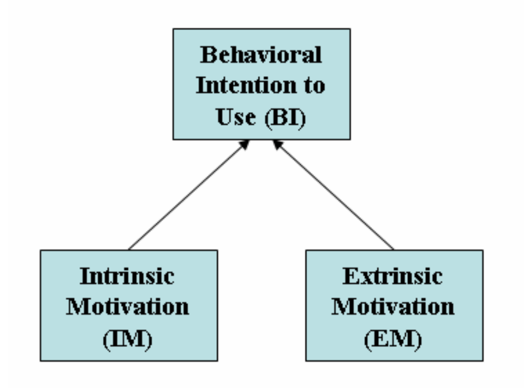


Figure 5; The Constructs of the Motivational Model

Extrinsic Motivation here can be seen as the willingness of using a system or technology in order to gain an external benefit from it, such as a monetary reward or an approving sign from a manager for example. Intrinsic Motivation on the other side, can be interpreted as the enjoyment that comes with the use of a system or technology. A higher IM indicates "a willingness to spend more time with a task, a lower anxiety, and better mood regarding a task, and a facilitation of volitional behavior" (Venkatesh, Speier 1999). The Motivational Model has some similarities with TAM, as previous research has pointed out (Cocosila, Archer et al. 2009). Many researches agree that Extrinsic Motivation and TAM's Perceived Usefulness are similar constructs. (Venkatesh, Morris et al. 2003) have put the aforementioned constructs under the same construct, namely 'Performance Expectancy'. In some other recent work, researchers found the MM more suitable for a particular situation than the more frequently used TAM. (Cocosila, Archer et al. 2009) have used the MM rather than TAM for example, as they argue that the MM captures the two main drivers for adopting and using a new IT application at a more general and in a broader way than TAM does. They also argue that the MM "looks at the broad picture of reasons to use *in principle* an incipient technology and not at the details of the use" and that the MM "is generally applicable in research due to its parsimony, allowing a clear delimitation of the extrinsic and intrinsic reasons for accepting the new technology."

2.3.4 Theory of Planned Behavior

Coming from the idea that behavior comes jointly from motivation (intention) and ability (behavioral control), (Ajzen 1991) extended the Theory of Reasoned Action (TRA) with the construct Perceived Behavioral Control (PBC) in order to formulate the Theory of Planned Behavior (TPB). TPB has its roots in psychology and is since its formulation in 1991 used in a wide variety of studies. In TPB, PBC has an effect on BI as well as a direct effect on Behavior. (Ajzen 1991) motivates this direct relationship with two reasons. Firstly, a person who perceives to be more in control will likely put more effort in achieving the desired behavior than a person who perceives to be less in control. However, intention also depends on Subjective Norm and Attitude, so two persons with different Perceptions of Behavioral Control can still have equally strong intentions. The second reason according to Ajzen is that, depending on the accuracy of the Perception, PBC can be a substitute for actual control. This way, PBC can be used to predict the probability of a successful behavioral attempt. (Taylor, Todd 1995) have combined TAM with PBC into a hybrid model in order to assess the role of prior experience on IT usage in a student information computing resource center. They argue that previous empirical tests with TAM have been conducted only on IT usage with experienced users. In their paper they address the issues (1) whether models such as TAM are able to predict usage of inexperienced users and (2) whether the determinants of IT usage are the same for experienced users as for inexperienced users. In order to do so, they use an augmented TAM which has many similarities with the model used by (Ajzen 1991). Their findings are (1) that the augmented model they suggest can be applied to understand the behavior of IT usage by experienced as well as inexperienced users and (2) that inexperienced users lay more emphasis on perceived usefulness rather than perceived behavioral control, this in contrary to experienced users.

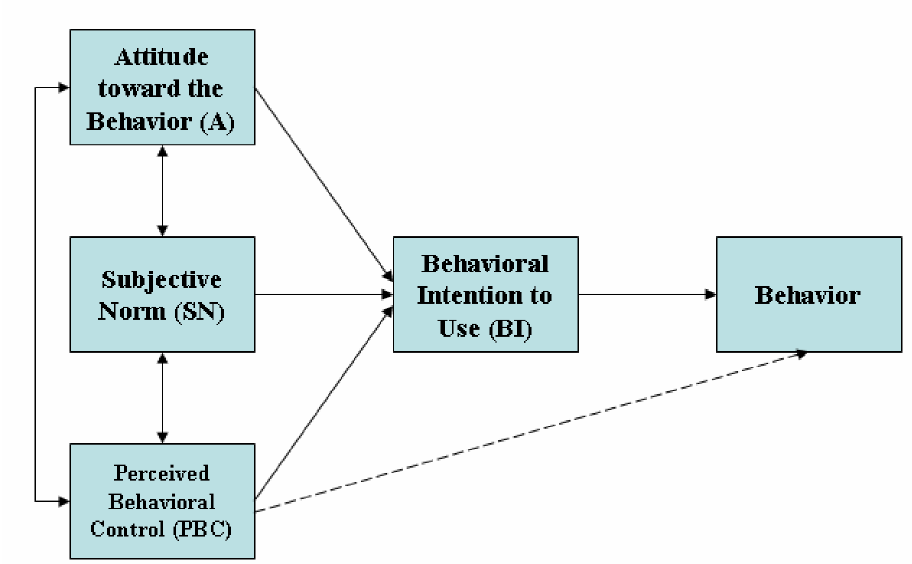


Figure 6; Theory of Planned Behavior

2.3.5 Innovation Diffusion Theory

Diffusion is the process by which an innovation is communicated through certain channels over time among the members of a social system (Rogers 1995). For that matter, most observers agree that diffusion is fundamentally a communication process. Seen over time, Diffusion is the period in which an extraordinary rate of adoption can be seen, between the early adopters and the later adopters. This sudden increase in adoption is the Diffusion process and causes the adoption curve to form an S-curve:

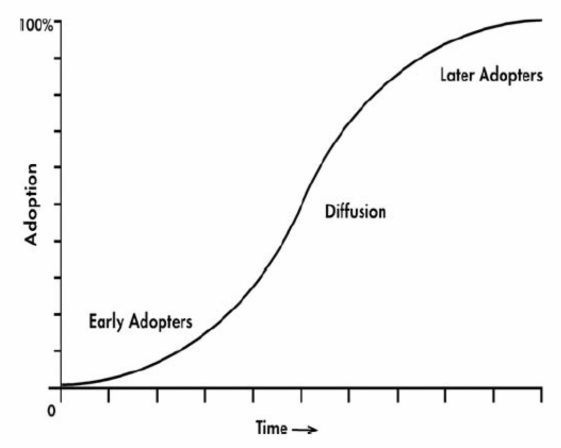


Figure 7; The Diffusion S-Curve

(Rogers 1995) identifies five categories of adopters along this curve (from early adopters to late adopters); innovators, early adopters, early majority, late majority and laggards. (Rogers 1995) explains the acceleration of adoption in the S- with a practice example. When the telephone just came out, there had to be a very first adopter of this new technology. This telephone was practically useless for the first buyer as he could not make any phone call to another person with a telephone. As soon as a second buyer bought a telephone as well, the usefulness of the telephone of the first buyer increased. This continues on and on and the more people start adopting a certain technology, the more benefits are gained by future and past adopters. The slope eventually decreases, as the mass of people perceive that 'everybody else' has adopted the new technology.

Diffusion of Innovations is comparable to the diffusion of news (Rogers 1995); however, Diffusion of Innovations goes a few steps further. The latter study not only investigates how something new gets awareness amongst people but also incorporates the changes in attitude, the rate of adoption and the decision-making process. Also, Diffusion of Innovations takes into account interpersonal communication more than any other communications study (Rogers 1995). In his work, Rogers defines innovation as "an idea, practice, or object perceived as new by an individual or other unit of adoption". Innovation Diffusion Theory (IDT) is a theory by (Rogers 1995) that has been used in many different types of settings. It started with Bryce Ryan and Neal C. Gross's study on diffusion of hybrid seed corn among Iowa farmers (see Rogers 1995 for the full story). Later Diffusion of

Innovations was used to study a variety of innovations, from medical drug studies to organizational innovation (Venkatesh, Morris et al. 2003). In their work, (Moore, Benbasat 1991) have adapted the theory in such a way that it can be used to learn about the perception of people for adoption of innovation in Information Technology. They formulated the seven constructs in order to use IDT to measure various perceptions of using an information technology innovation (Moore, Benbasat 1991):

- Relative Advantage; the degree to which an innovation is perceived as performing better than the current system.
- Ease of Use; this construct was named ‘complexity’ by Rogers but Moore and Benbasat renamed the construct to be consistent with other technology adoption models. Ease of use here means the degree to which an innovation is perceived as being difficult to use.
- Image; the degree to which use of an innovation is perceived to enhance one's image or status in one's social system.
- Visibility; this construct is adapted by (Venkatesh, Morris et al. 2003) from the work of Moore and Benbasat. We describe this construct here as well since we are working towards the unified view Venkatesh et al. have provided in their research. Visibility here means the degree to which one can see others using the system in an organization (Venkatesh, Morris et al. 2003). See also (Plouffe, Hulland et al. 2001).
- Compatibility; the degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters.
- Results Demonstrability; this is a concatenation of the original constructs ‘Observability’ and ‘Communcability’ and represents the Tangibility of the results of using an innovation.
- Voluntariness of Use; the degree to which use of the innovation is perceived as being voluntary, or of free will.

2.3.6 Model of PC Utilization

Adapted from (Triandis 1980) ‘s theory on human behavior, the Model of PC Utilization (MPCU) uses a subset of Triandis’ work to test his theory in context of PC use (Thompson, Higgins et al. 1991). In contrast to many other technology acceptance models, the MPCU does not include Behavioral Intentions as a factor of analysis. Rather, the model uses a subset of Triandis’ model in order to predict PC usage directly.

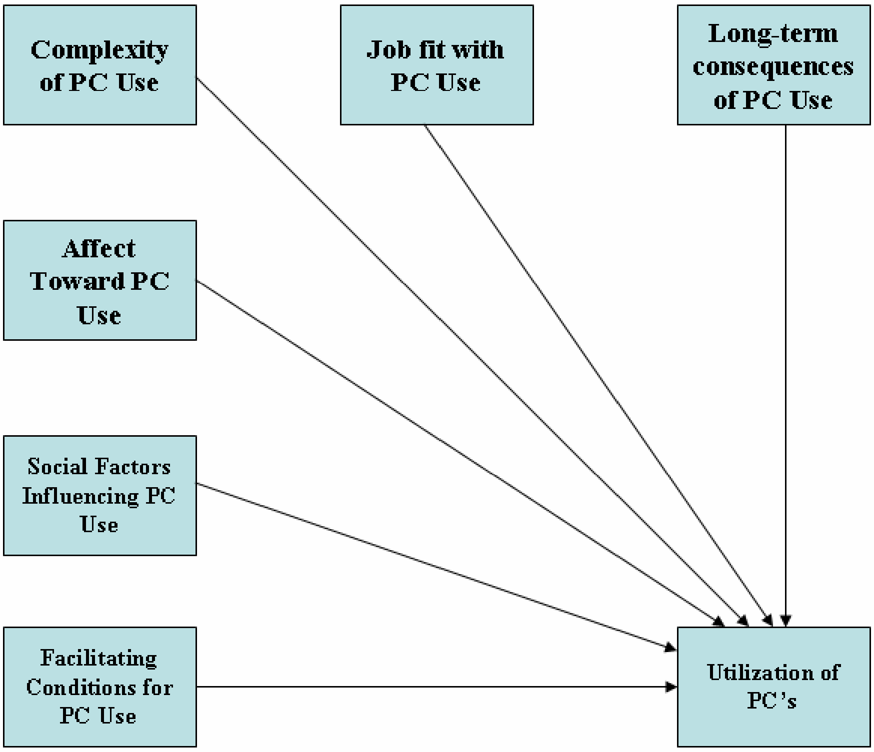


Figure 8; Factors Influencing the Utilization of Personal Computers

In MPCU we can identify several constructs that have a direct impact on the Utilization of PC's:

- Long-term Consequences: "Outcomes that have a pay-off in the future".
- Job-fit with PC Use: "The extent to which an individual believes that using [a technology] can enhance the performance of his or her job" (Thompson, Higgins et al. 1991)
- Complexity of PC Use: "The degree to which an innovation is perceived as relatively difficult to understand and use" (Thompson, Higgins et al. 1991)
- Affect toward PC Use: "Feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act" (Thompson, Higgins et al. 1991).
- Social Factors Influencing PC Use: "The individual's internalization of the reference groups' subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations" (Thompson, Higgins et al. 1991)
- Facilitating Conditions: (Triandis 1980) describes the factor Facilitating conditions as "objective factors out there in the environment, that several judges or observers can agree make an act easy to do". In the context of IS use, "the provision of support for users of PCs may be one type of facilitating condition that can influence system utilization" (Thompson, Higgins et al. 1991).

2.3.7 Social Cognitive Theory

Social Cognitive Theory is a widely accepted theory on human behavior and relies on the premise that an individual's environmental circumstances, an individual's personal factors such as personality and demographic factors and an individual's behavior are reciprocally determined. (Bandura 1986) calls this phenomenon 'triadic reciprocality'. It means that an individual will choose an environment based on his personal preferences and experiences, and at the same time the personal preferences and experiences will be influenced by the environment. Also, behavior will be determined by the environmental characteristics but the environment itself will be influenced by the behavior of the individual. Finally, an individual's behavior will be partly determined by the individual's personal characteristics, which in turn will be influenced by the behavior of the individual.

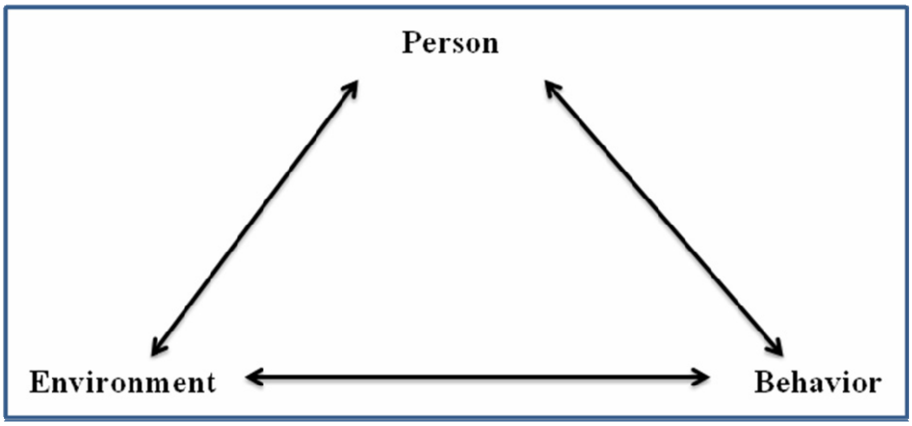


Figure 9; Triadic Reciprocality

From Social Cognitive Theory, one of the most powerful theories of human behavior, (Bandura 1986), (Compeau, Higgins 1995) studied the impact of Self-efficacy on individual reactions to computer technology. Self-efficacy can be defined as "the belief that one has the capability to perform a particular behavior" (Compeau, Higgins 1995). Computer Self-efficacy then is defined as 'a judgment of one's capability to use a computer'. To keep the triadic reciprocality from Bandura, the model of Compeau and Higgins for their study incorporated several other variables besides Computer Self-efficacy into their model to predict the individual usage of computers:

- Encouragement by others; how people perceive their own capabilities of performing a certain behavior is partly determined by the opinions of others from the environment of the individual. Also, when an individual gets encouraged by others from the environment, the individual will expect that these people at least will be pleased by the behavior (usage). Therefore, Encouragement by others is theorized to affect the individual's Computer Self-efficacy as well as the Outcome Expectations.

- Others' Use; observing others' behavior will lead to behavior modeling (Compeau, Higgins 1995). Just as Encouragement by others, Others' Use is therefore theorized to affect the individual's Computer Self-efficacy as well as the Outcome Expectations.
- Support; having an option to get assistance will lead to expect better outcomes and will raise the individual's Computer Self-efficacy.
- Outcome Expectations; what an individual expects to be the outcome of a behavior is theorized to influence the affect the individual has with that behavior. When someone expects to get rewarded highly for a behavior, the individual will feel more affect towards that behavior because people like to get rewarded. On the same note the Outcome Expectations will have a positive influence of the actual usage.
- Affect; how much an individual likes a certain behavior (such as computer usage) will affect that behavior.
- Anxiety; opposite to Affect, the more Anxiety an individual feels for a certain behavior, the less that behavior will be performed. People tend to avoid behaviors that come with a feeling of anxiety (Compeau, Higgins 1995).

These relationships between the variables of the research model of (Compeau, Higgins 1995) are visualized in figure 10:

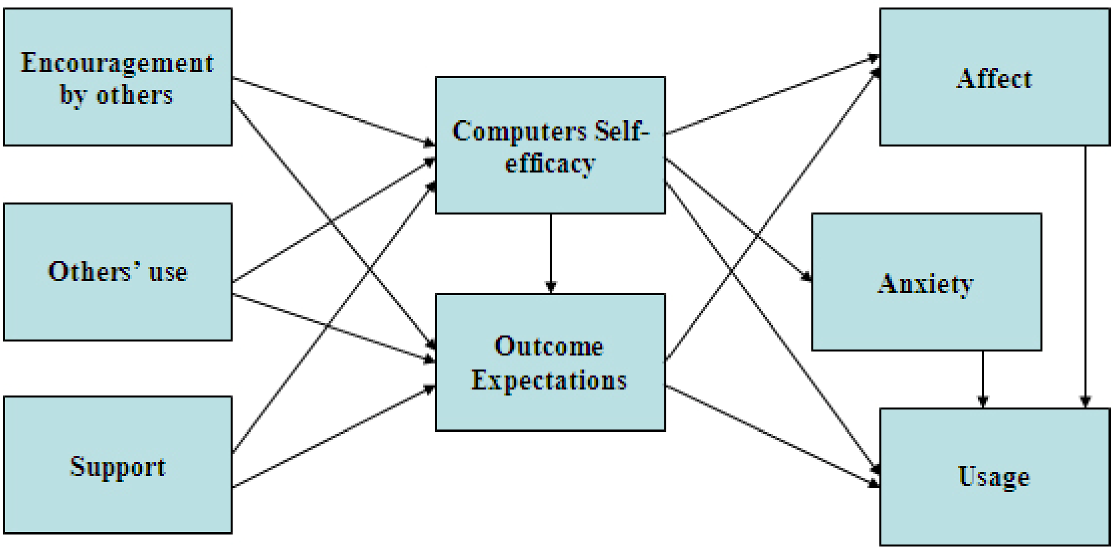


Figure 10; The research model of Compeau and Higgins

2.3.8 Unified Theory of Acceptance and Use of Technology (UTAUT)

Previously discussed models to study the acceptance of technology have been unified into a model that uses the elements of the reviewed models that seemed to have a significant impact on intention or usage (Venkatesh, Morris et al. 2003). In their study, they give an overview of the acceptance theories and models that had been surfaced until then, they assess the eight discussed models reviewed and compare them, and from there they propose UTAUT and empirically validate their model. For an overview of the used acceptance models and theories to formulate UTAUT, we refer to Appendix A.

In UTAUT, four constructs have been assumed to serve a role as a determinant of intention to use technology, namely:

- Performance Expectancy
- Effort Expectancy
- Social Influence
- Facilitating Conditions

Whereby 'Facilitating Conditions' also serves as the only direct determinant of use of technology. To get a better understanding of UTAUT, we will break down the model into these concepts and discuss them and their moderating variables in the upcoming sections.

2.3.8.1 Performance Expectancy

The concept from the reviewed models that is the strongest predictor of intention is Performance Expectancy (PE). PE is defined as 'the degree to which an individual believes that using the system will help him or her to attain gains in job performance' (Venkatesh, Morris et al. 2003). The moderating variables on PE are Gender and Age.

2.3.8.2 Effort Expectancy

As with TAM Ease of Use explains how individuals perceive the use of technology will be free of effort, Effort Expectance (EE) is in UTAUT defined as 'the degree of ease associated with the use of the system' (Venkatesh, Morris et al. 2003). The constructs to form EE are Perceived Ease of Use (TAM/TAM2), Complexity (MPCU) and Ease of Use (IDT). EE has three moderating variables in UTAUT, namely Gender, Age and Experience.

2.3.8.3 Social Influence

Where TRA and TAM2 had the determinant 'Subjective Norm', UTAUT uses the term 'Social Influence' (SI) to define 'the degree to which an individual perceives that important others believe he or she should use the new system' (Venkatesh, Morris et al. 2003). Social influence is a relatively complex concept in UTAUT. The work of (Venkatesh, Morris et al. 2003) suggests that Gender, Age, Experience and Voluntariness of Use are all moderators of the relation between Social Influence and Behavioral Intention. Social Influence, according to them, has more impact with older workers, especially women, during the early stages of experience and is more likely to have a bigger impact under mandatory settings.

2.3.8.4 Facilitating Conditions

Facilitating Conditions is the only concept from UTAUT that has not used any concepts directly from TRA or one of the TAM models. In UTAUT, Facilitating Conditions is defined as 'the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system' (Venkatesh, Morris et al. 2003). It differs from the other constructs in that it has no significant influence on Behavioral Intention. The effect is expected to be even stronger when the moderator Experience increases; users might find different ways to use the system. Finally, the physical and mental limitations that come with higher age will, in the context of complex IT, also have a moderating effect on this relation.

2.3.8.5 The moderators Gender, Age and Experience

In UTAUT, Venkatesh et al. suggest the existence of four key moderating variables; Gender, Age, Experience and Voluntariness of Use. In their research they distinguish between voluntary and mandatory use of information systems. We believe the use of Twitter is a service that will most likely be used in voluntary settings only, therefore we keep Voluntariness of Use out of our research model. The other moderators are variables that have shown to be of moderating influence on the main constructs and therefore we will take them into account in this research. In some situations an effect can be stronger or weaker for men or for women with a certain age. Also, experience can play a role in the effect a construct has on the Behavioral Intention or Use Behavior. In the final section of this chapter (Section 2.4), where we define our hypotheses, we go deeper into the moderators of our research model.

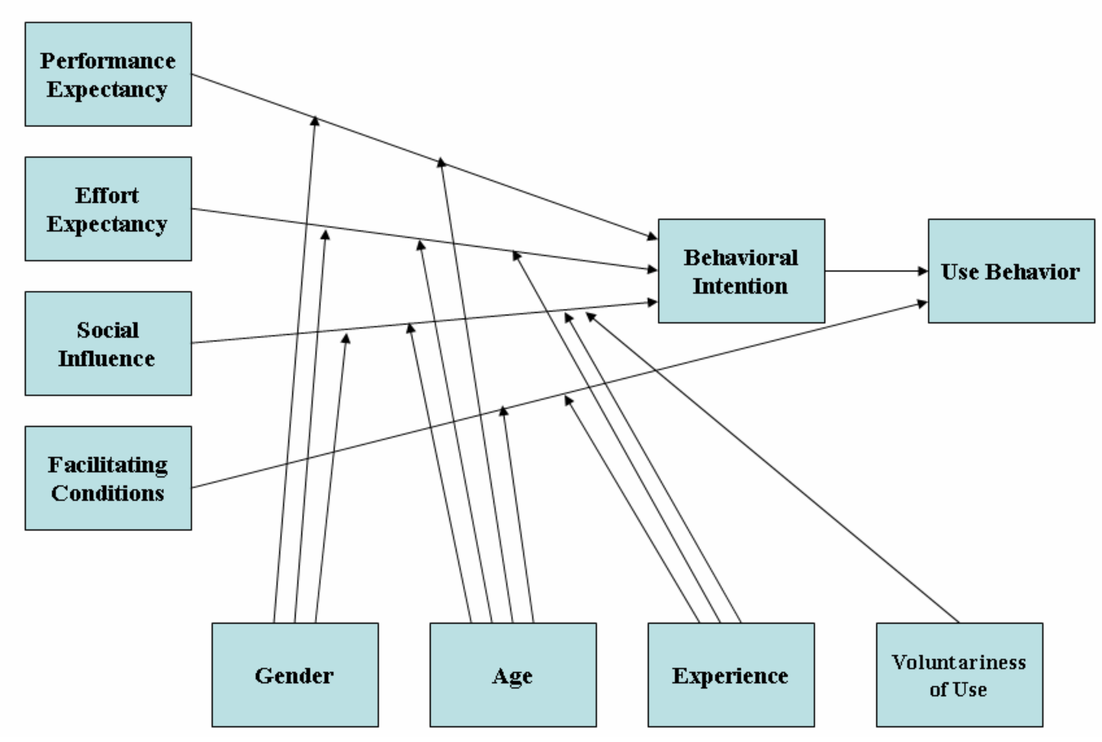


Figure 11; Unified Theory of Acceptance and Use of Technology

The work of Venkatesh et al. will serve as the base of our research. However, we will use UTAUT in reverse to explain the success in acceptance of Twitter.

2.4 An introduction to Web 2.0

The purpose of our research is to apply the UTAUT research model to Web 2.0 applications. In the next few sections we describe what Web 2.0 is according to current scientific literature. Then before we describe current Web 2.0 applications we will describe a conceptual framework with which we define Web 2.0 even further. Then we provide an overview of current types of Web 2.0 applications and finally we the application of our focus, Twitter, more in-depth.

2.4.1 What is Web 2.0?

In our study, we want to define Web 2.0 applications so we can distinguish them from Web 1.0 environments. In order to do so, we firstly introduce broader definition of Web 2.0. (Kim, Yue et al. 2009) define Web 2.0 as 'an umbrella term that describes a set of ongoing development of Web generations which have layered conceptual ideas and newer applications/services that current technologies push and market demands pull.' (Murugesan 2007) describes Web 2.0 by comparing it to compare it to its predecessor, Web 1.0. From that perspective, he says that 'Web 2.0 harnesses the Web in a more interactive and collaborative manner, emphasizing peers' social interaction and collective intelligence, and presents new opportunities for leveraging the Web and engaging its users more effectively'. From these two definitions we define Web 2.0 as

'An umbrella term for the generation of highly interactive and collaborative Web services that are pushed by new technologies, business strategies and social trends and pulled by new market demands'.

2.4.2 The Web 2.0 conceptual Framework

With their broad definition, (Kim, Yue et al. 2009) also provide a conceptual framework from a holistic perspective in order to get a better understanding of the topic Web 2.0. In this framework, they distinguish four different Web 2.0 layers, which are from bottom to top:

- Technology Layer; this Layer incorporates all available web technologies that provide possibilities to create principles such as Semantics (a terminology standard and system to logically organize and link data) and Interactivity Responsiveness (updating website content based on interactivity with the user quickly). These amongst other principles made possible by the latest technology causes a 'Technology Push' upwards. These technologies such as AJAX, XML, Content Management Systems, the Semantic Web and others make it possible to create a whole range of new internet principles.

- Principle Layer; the technologies from the Technology Layer allow new Internet principles to be created. Principles such as Collaboration, Participation, Social Networking and Rich User Experiences are now possible and form the second layer.
- Application Layer; this layer contains the actual applications as we know them now, such as Social Networks (Facebook, Hyves, LinkedIn), (micro) Blogs, Podcasts, Mashups etc. More details on Web 2.0 applications can be found in Section 2.4.2.
- (User/Market) Driver Layer; this layer is the layer which causes the 'Demand Pull' from users and markets. Users of the Internet continually change their demands such as the ways they like to share information with others or the way they interact with a website on the internet.

This framework allows us to chunk up the broad definition that Web 2.0 has. This study investigates the Principle Layer and the Application layer. The Principle layer defines the principles behind Web 2.0 applications, and these principles as we will assume, have their implications on how the applications are being accepted by users. Before we will narrow down which application we use for this research, in the next section we provide an overview of current Web 2.0 application as they exist currently on the internet.

2.4.3 Web 2.0 applications

In this section we will provide an overview of some Web 2.0 application groups that have been defined by (Murugesan 2007). Per group we will discuss some examples of application that are on the internet today.

2.4.3.1 Blogs

Blogs, an abbreviation for Web logs, are web sites where people can share thoughts, opinions, suggestions and comments (Murugesan 2007)(Li, Kishore 2006). These opinions and thoughts can be shared through text (which is the case in most blogs), videos (which are then called videoblogs or vlogs) or audio (such as Podcasts). Relatively new is live blogging (www.coveritlive.com) , where new blogs that you write are actually streamed onto your web site. This way you can let your readers know real-time what is going on, rather than having to type the text first, then publish it and refresh the page in order to display the blog.

A term that is being referred to often on the internet is the *blogosphere.* This is the collection of all blogs on the internet, combined into one big community or social network. This is possible due to the unique aspect of blogs that they can link through to other blogs, which creates these communities and relationships between *bloggers.*

Finally, blogs can also be syndicated; that means that every time a blog gets updated by the author, the subscribers to that weblog get the update automatically (Murugesan 2007). We will go deeper into syndication in the next section.

2.4.3.2 Really Simple Syndication

Really Simple Syndication, or RSS, is the technology that allows users to get updates from the blogs and casts that they have subscribed to automatically, without having to visit the web sites. The update information (the feed) is being 'piped' to the users computer in a process known as syndication (Anderson 2007). The users therefore use software installed on their computers named 'feed readers' or 'aggregators'.

The main advantage of RSS is that users do not have to surf over the web in order to retrieve the latest information and updates from their subscriptions; instead, they can read, see and hear everything within one single computer program.

2.4.3.3 Wikis

Making use of the collaboration principle, wikis are information systems that are created and edited entirely by its users. With a special markup wiki-language, it lets every user add and edit content. The term 'wiki' is derived from the Hawaiian word *wikiwiki,* which means fast or quick (Murugesan 2007). Some specific wiki features are:

- Wikitext; the markup language that provides the fundament for new content, the linking structure of wikis and formatting of the text (Murugesan 2007)
- Unlike blogs, wikis often have a history button that allows users to see the previous version(s) of current content (Anderson 2007).
- Wikis usually have simple looks and site structures, due to the markup language and desire of wikis looking consistent. The site structures are relatively flat which keeps the navigation simple (Murugesan 2007).
- Direct contribution with open access and high flexibility to content, from different groups and/or users from different locations around the globe, which increases communication efficiency (Murugesan 2007, Anderson 2007)

Also in business environments, wikis are being used. According to (Majchrzak, Wagner et al. 2006), there are three major benefits of using wikis in a corporate environment: Benefits to enhanced reputation, benefits to making work easier, and benefits to helping an organization improve its processes. In contrast to these advantages of wikis, there have been some cautions to wikis due to their openness and flexibility (Anderson 2007).

2.4.3.4 Mashups

Mashsups are web sites that can combine data from multiple sources into one page (Murugesan 2007). The main advantage of having multiple sources of data showed on one page is that you do not have to visit all the pages separately, but rather have the latest information from your favorite websites, all displayed at once on an enhanced user interface.

From a programmer's perspective, Application Programming Interfaces (API's) can be used to integrate previously programmed applications into innovative, combined multi-services with easy-to-navigate user interfaces. This way of combining already existing applications rather than rewriting programs from scratch is a fundamental Web 2.0 principle and mashups are typical Web 2.0 applications that use the available resources to their benefit.

Google Maps is such an API that has been used a lot to create Mashups. From pointing out on a map where to buy second hand computer games to see where the best surfing spots are in France; Google Maps is the application to use. When we look at the API's and Mashups from www.programmableweb.com, which has a huge database of Mashups and API's (on August 4th 2009 they had 1407 API's and 4220 Mashups), we see that their mostly used API of all time is Google Maps (45%). Twitter has with 6% the 5th spot in this ranking, after Flickr (11%), Youtube (10%) and Amazon (7%).

However, when we look at the situation today, we see a shift towards other API's as well. We see that some API's have lost popularity, such as the API's of Flickr (from 11% all time to only 4% today) and del.icio.us (from 3% all time to not even being mentioned on today's popularity list). Some other API's have grown in popularity, such as Google (3% all time but today responsible for 6% of the Mashups created) and LastFM (at most 4% of all time and these days responsible for 8% of the Mashups created). Especially the API from Twitter seems to have gained popularity with 20% of the Mashups created today being made with the API from Twitter. For more info and more current updates the reader can look on the web, www.programmableweb.com.

2.4.3.5 Tags and tag clouds

Tags are keywords attached to (micro)blogs or web pages in order to be found more easily by applications such as del.icio.us (Murugesan 2007). Tags are relevant to this study because they are used in tweets in Twitter as well, in order to give users the opportunity to get the latest updates of fields of their interest (marked by tags) automatically, for example by news feeds.

Tag clouds are a visualization of the popularity of tags. In order to make it easy for users to see which tags are more popular, the tag fonts are sized according to their popularity and displayed in an alphabetical order. The more popular a tag is, the bigger the font it will be displayed in.

2.4.4 Twitter and Micro-Blogging

Twitter is a micro-blogging service where users can give following users updates on their current activities by posting short text messages (SMS) which are messages of at most 140 characters. The short length of these messages is the main concept that distinguishes micro-blogging applications from other OSN's (Krishnamurthy, Gill et al. 2008, Günther, Krasnova et al. 2009, Java, Song et al. 2007). These messages can be uploaded onto a users' profile by sending an SMS by mobile phone or by editing the current status on the website of Twitter or through other, linked social networks such as Facebook. Founded in October 2006, Twitter was written in the language 'Ruby on Rails'. The reason why they have chosen Ruby on Rails is because they can update the site easily and frequently:

'Rails provides skeleton code frameworks so we don't have to re-invent the wheel every time we want to add something simple like a sign in form or a picture upload feature.' (http://twitter.com/about#about)

Prior research has been conducted on how and why Twitter is being used in organizational settings (Günther, Krasnova et al. 2009) as well as why it is being used for private purposes (Java, Song et al. 2007). Gunther et al. have modified and extended the UTAUT model in order to assess microblogging applications such as Twitter adoption in an organizational environment. Their findings from four focus groups have indicated that several other concepts such as reputation, expected relationships, expected codification effort, signal-to-noise ratio, and privacy concerns are relevant concepts to the microblogging applications. The modification and extension of the UTAUT model were based on these concepts (Günther, Krasnova et al. 2009). No empirical testing was conducted however.

Java et. al also have conducted research on Twitter. In their study, they have used a dataset that has been gathered over 2 months from the 'public timeline' of Twitter. With observing the structure of the networks and looking at the most frequently used words they have extracted the user intentions of the dataset and discussed several intentions of the Twitter users (Java, Song et al. 2007):

- Daily chatter; this is the most common use of Twitter.
- Conversations
- Sharing information / URL's
- Reporting news

Also, their findings indicated that there are three main categories of users in the Twitter network. The first group of users contains those people that update their posts regularly or infrequently and have a lot of followers. The nature of their posts is valuable to their followers. Java et. al call this group ‘information source’. The second group, ‘friends’, is the biggest group and consists of many subcategories. The last group, ‘information seekers’, are users that tend to follow other users regularly, but might post rarely himself. (Krishnamurthy, Gill et al. 2008) later confirmed the existence of three distinguishable groups but they gave them different names; ‘broadcasters’, ‘acquaintances’ and ‘miscreants or evangelists’.

2.4.4.1 Hashtags

Twitter has no system to categorize tweets. Therefore, Twitter users came up with the idea of using ‘hashtags’ in tweets. These hashtags are noted by the hash-sign (‘#’), followed by the name of the category the tweet should be shown in. For example, the hashtag ‘#daretoask’ is meant for Tweets that that demand something from other people, like filling out a survey.

2.5 Literature review summary

Use of Computers and Technology has been a field of interest for researchers ever since computers exist. To know what factors drive the acceptance of existing or new technologies may help managers and designers; it gives insight on how to design these technologies as well as on how to manage users and technologies in such a way that the Information Technology is being used successfully. Many researchers have made an effort to develop instruments and models to measure user acceptance of technologies in wide varieties of environments. New determinants of Intention to use technologies have made their appearance throughout the years and many of these determinants eventually made their way into the Unification of some important Technology Acceptance models; the Unified Theory of Acceptance and Use of Technology, or UTAUT. In this model, conceptual and empirical similarities between different factors within the models have functioned as glue between those factors and from there the unified theory was formulated. This model takes the constructs Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions as predictors for the Intention to Use a Technology.

We defined Web 2.0 as ‘an umbrella term for the generation of highly interactive and collaborative Web services that are pushed by new technologies, business strategies and social trends and pulled by new market demands.’ Within this umbrella we have seen many applications that form the application layer of the Web 2.0 framework of (Kim, Yue et al. 2009). One of these applications falls within the category of ‘micro-blogging services’, Twitter. Twitter is a service where users can post messages of maximum 140 characters onto their account by posting this on the website or by sending the message by a mobile phone. Followers of these users can then see instantly what the user is currently doing. The service is being used for daily chatter, reporting news, conversations and for sharing information with others.

2.6 Formulation of hypotheses

In this section we describe the process of developing our hypotheses. For every construct of our research model we describe the hypothesized relationships, adapted from the UTAUT model for the context of the use of Twitter.

2.6.1 Performance Expectancy

Performance Expectancy measures to what extent an individual believes the Technology is improving his or her job performance. Since 'Daily chatter' is the most common use of Twitter, we can hardly say that Twitter is used for professional purposes, so there is no professional output that users of Twitter, nor we, will be able to assess. However, we can say that the 'job' that the technology should (or should not) enhance is 'Daily chatter', since that is the purpose most people are using Twitter for. When we look at business purposes, we can say that people are using the technology to improve their job performance, without actually knowing what their job tasks are. Therefore the term 'job performance' is a generalized term which counts for many researches within organizational settings. However, this research is not within an organizational setting. With the use of Twitter, we know what the job task actually is in most cases, namely 'daily chatter'. This is a social setting, rather than an organizational setting. If we now want to generalize the purpose of the Twitter 'information system' in terms of job performance, we consider 'interpersonal communication' as the Job that the Technology of Twitter should be performing. From that perspective we investigate whether users of Twitter think their use of the micro-blogging service enhances their communication with others. That way we measure the perceived Usefulness of Twitter. (Venkatesh, Morris et al. 2003) also found that PE is the strongest predictor of intention for all individual models, so we expect PE also to have a positive effect on the intention to use the technology.

H1: Performance Expectancy will have a positive influence on Behavioral Intention to use Twitter.

2.6.2 Effort Expectancy

Effort Expectancy is defined as the degree of ease associated with the use of the system (Venkatesh, Morris et al. 2003). The construct of Effort Expectancy is moderated by Gender. The reasoning here is that Effort Expectancy can be more striking for women than for men. Cognitions related to gender roles could possibly drive these differences between men and women in their perceiving of Effort Expectancy. Also, the older people are, the more difficulties they experience with the more complex stimuli. Therefore, Age also moderates Effort Expectancy in such a way that older people will attach more value to Effort Expectancy than younger people. Finally, the more experience an individual has with the use of a technology, the less value that individual attaches to the ease of use of that technology. According to (Venkatesh, Morris et al. 2003), the effect from Effort Expectancy on Intention to Use will increase with as the individual gains more experience with use of the system. We will test the moderating effects of Experience, Age and Gender in this research and we hypothesize that Effort Expectancy will have a positive influence on the Behavioral Intention to use the technology.

H2: Effort Expectancy will have a positive influence on Behavioral Intention to use Twitter.

2.6.3 Social Influence

Social influence is the degree to which an individual perceives that important others believe he or she should use the system (Venkatesh, Morris et al. 2003). Because daily chatter is a social activity, the construct of Social Influence might be an important factor in explaining the Intention to use Twitter. In previously discussed acceptance models (TRA and TPB) Social Influence was described as 'Subjective Norm'. Theory suggests that women tend to be more sensitive to others' opinions (Venkatesh, Morris et al. 2003) and therefore we gender might moderate the effect from Social influence on Intention to use a new technology in such a way that the effect will be stronger for women. This effect however, will decline as experience increases (Venkatesh, Morris et al. 2003). The reasoning behind this is that as people use a system more often, they might become more independent on what others think of their use of the system. As a last moderator, Age might have a positive effect on the relationship between Social influence and Intention to use, as prior research has pointed out that "affiliation needs increase with age" (Venkatesh, Morris et al. 2003), which means that the older people are, the more they need to have confirmation from their social circles in order to use a new technology. Again, this effect declines with more experience. We will test the effects of aforementioned variables in our model and our hypothesis for Social Influence is:

H3: Social Influence will have a positive influence on Behavioral Intention to use Twitter.

2.6.4 Facilitating Conditions

Web 2.0 applications involve the users with creating content (Kim, Yue et al. 2009). This increase in involvement might lead to an increase in perceived control with users of these information systems, which in turn would mean an increase in user acceptance (Baronas, Louis 1988). This is even more likely in case of experienced users, as we have seen with the augmented TAM model of (Taylor, Todd 1995). So we expect experience to have a moderating effect on the relationship between Facilitating Conditions and Behavioral Intention. Also, given the increasing cognitive and physical limitations coming with age, Age might have moderating effect on the relationship between Facilitating Conditions and usage. Foremost, like (Venkatesh, Morris et al. 2003) have suggested in their theory, we hypothesize that Facilitating Conditions will not have a significant effect on Behavioral Intention, but there will be a significant relationship between Facilitating Conditions and the actual usage of Twitter:

H4: Facilitating Conditions will ***not*** *have an influence on Behavioral Intention to use Twitter*
H5: Facilitating Conditions will have a positive direct influence on the Usage of Twitter.

2.6.5 Behavioral Intention

This research tests the effects that constructs of UTAUT have on the Intention to use Twitter. The actual Usage has exploded in the last few years as we have seen in the literature review and we are looking for explanations for this growth. However, we must assume first that the Intention to Use Twitter also has a significant relationship with the actual usage. So we will assume that the intention to use the system will also have a positive influence on the actual usage of the system.

H6: Behavioral Intention will have a positive influence on the actual Usage of Twitter.

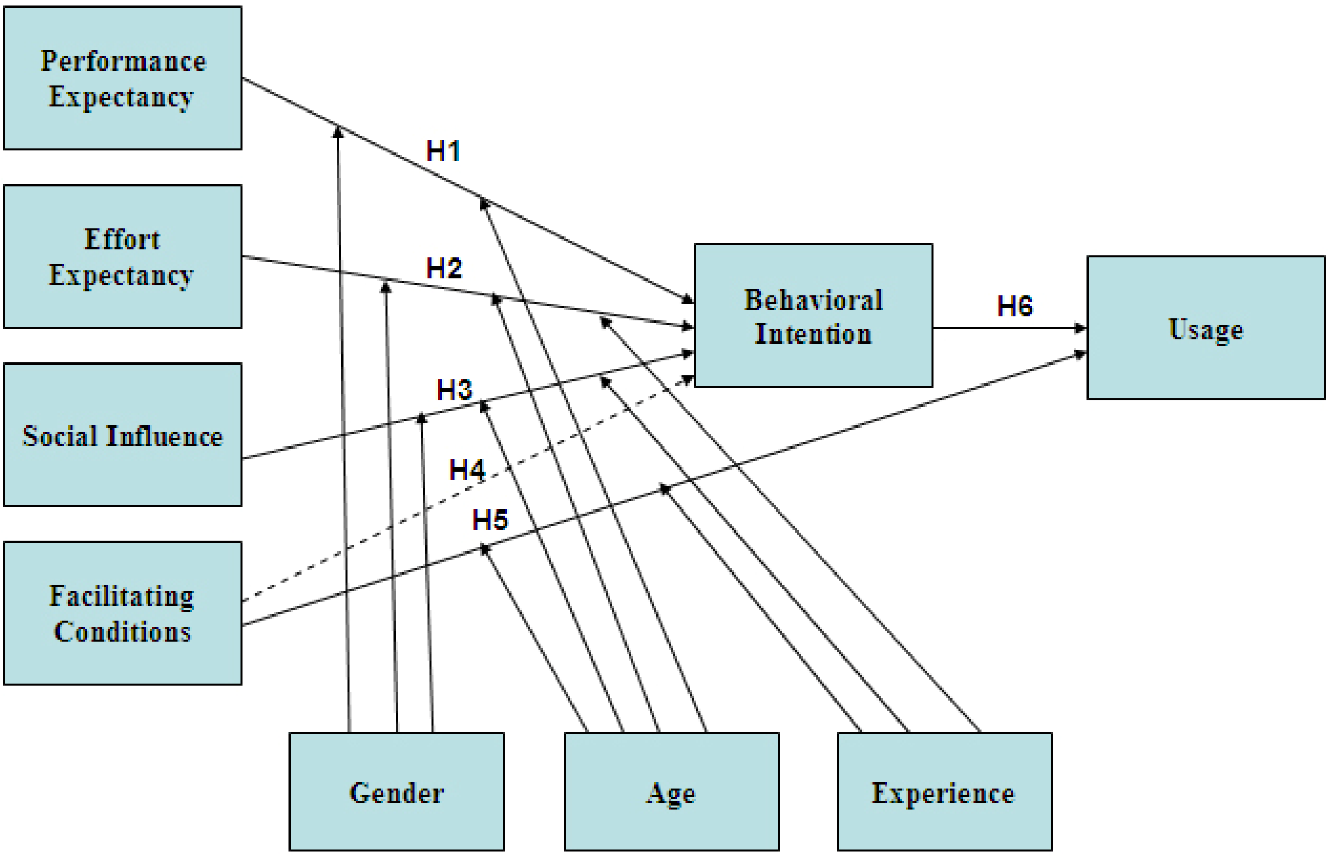
3 Methodology

In this section we outline the methodology by which we conduct our research. We do this so this research can be reproduced by other researchers if needed or desired. Firstly, we describe the constructs we use in our research model. Then we describe the respondents who will participate in our research and how we reach them. Then finally we describe the process of forming our online survey and we elaborate on why and how we conduct an online survey.

3.1 The research model

As mentioned in the Introduction (Chapter 1), the micro-blogging service Twitter has gained enormous popularity in the recent past. Since this increase in popularity points out that the Use Behavior has increased this much, we will use the UTAUT model (See Section 2.2.3) in reverse to explain this increase in Use Behavior.

Figure 12; Our research Model with Hypotheses



3.2 Data collection method

We choose to use an online survey in order to collect the data for this research. An online survey has the advantages of having low cost, being fast and efficient, direct data entry and a wide geographic reach (Sue, Ritter 2007). There are some disadvantages to conducting a web survey; collecting data on the internet with a survey usually comes with a coverage bias, there is a reliance on software and also we don't know who is responding to the survey. Since we want to use users of Twitter in our research, some of these disadvantages will be diminished. The coverage bias of the online population not representing the total population is not relevant in our research because we want to generalize our conclusions to users of Twitter. We are purely interested in how Twitter gained so much popularity and we simply cannot explain that by asking people questions about it, who do not use the service.

3.3 Survey method

In order to have our data gathered in an efficient and reliable way, we make use of the service 'SurveyGizmo' (available at http://www.surveygizmo.com). They have been providing online survey facilities since 2005 and they offer students a free to use Student account. There is some advertising at the bottom of the survey page in return. The data gathered with the surveys will be stored on their servers and is available in different formats, making it easier to analyze the data with different statistical programs and methods.

3.3.1 Shortening the link of the survey

In order to place the survey online and especially in Twitter messages, we reduced the length of the hyperlink to the survey with an application called Bit.ly. Bit.ly creates very short links from URL's that take a lot of characters. The link of our survey, which had the original link of http://app.sgizmo.com/s/survey_slug.php?sg_id=234351&sg_slug=the-success-story-of-twitter, was translated by bit.ly into 'bit.ly/9F5228'. This link was more appropriate to post in a Tweet online since it did not take up as much of our 160 characters as the original link. Many tweets seen on Twitter use these shortened links in order to place URL's on Twitter.

3.4 Subjects

The subjects we use are all users of Twitter. They can be men or women, young and old, experienced or inexperienced, as long as they are familiar with the use of micro-blogging service Twitter.

3.4.1 Acquiring subjects

There are several ways in which we acquire the subjects to fill out our survey. Firstly, we send out a Tweet over the Twitter network to ask users of the micro-blogging site to fill in our survey. We use hastags in order to display our tweets on groups. The hashtags we are using are '#daretoask' and '#durftevragen'. The latter one is the same as the first, but then a Dutch version of the group. Secondly, we send messages over other social networks such as Facebook and LinkedIn in order to ask people who also use Twitter to fill out the survey.

3.5 The survey

In order to collect our data, we take the items from (Venkatesh, Morris et al. 2003) to formulate the questions for the survey. However, some of the items are specifically meant for a business environment. Especially in measuring Performance Expectancy, many items are made from a business perspective. Since Twitter is a social activity and there more often not an intention to gain money from the use of Twitter, we cannot ask people to rate items such as 'The use of Twitter will increase my chances of getting a raise'. This example is item 7 on the Outcome Expectations survey from (Compeau, Higgins 1995), measured in UTAUT for Performance Expectancy. Therefore, we will alter some of these questions in order to be still able to measure the constructs of UTAUT.

3.5.1 The altered questions

In this section we provide explanations for why we altered items taken from UTAUT, in order to adapt the survey for measuring the use of Twitter. Firstly, we change the words 'the system' from all questions for 'Twitter'. Since the participants in this study are all users of Twitter, we assume that they know the name of Twitter so we do not have to name it 'the system'. In the parts underneath the titles following, will be the reasoning behind the changes we make. All (altered) items used for this research can also be found in Appendix B.

3.5.1.1 OE7; If I use Twitter, I will increase my chances of getting a raise

As explained in Section 3.5, the use of Twitter is mainly a social activity; 'daily chatter' is the most commonly reason to use Twitter (Java, Song et al. 2007). Therefore, we cannot ask users of Twitter about raises in monetary terms. However, we can ask people whether the use of Twitter gains them a 'social boost'. A 'social boost' is interpreted differently by any individual. Therefore it would be invalid for us to make up our own words fot this social raise. For this reason we keep the generic term of 'social boost' instead of a monetary 'raise'.

3.5.1.2 SF2: The senior management of this business has been helpful in the use of the system.

In this question from Social Factors to determine Social Influence, a senior management is involved. In the use of Twitter however, there is no senior management available. We could interpret the senior management here for the advice that the website of Twitter comes with; however, that would be again something we would just assume. Instead, we choose here to replace the question with another question from Social Factors that can be altered in such a way that it is more likely that the core of the question remains the same. We do this by looking at the item loadings from the Partial Least Squares (PLS) test within (Venkatesh, Morris et al. 2003).

Within Social Influence, all of the Social Factors items have higher loadings than the Image items. When we look at the item of Social Factors with the highest loading after SF2 and SF4 (the ones that are used in UTAUT originally), we find SF3: “My supervisor is very supportive of the use of the system for my job.” This item however, is again very hard to put in the Twitter context, due to the words ‘supervisor’ and ‘job’. Again this is an item specifically meant for business environments. The item that follows after SF3 is SF1: “I use Twitter because of the proportion of coworkers who use Twitter.” Here the only word that is not suitable for the Twitter environment is ‘coworkers’. However, coworkers can be seen as people who also might use the system from the same environment. That indicates that the word coworkers can be replaced by the word ‘friends’, since friends are also people who might use Twitter from the same environment as the individual.

3.5.1.3 SF4: In general, the organization has supported the use of the system.

With this item, we need to alter the word ‘organization’ since it is again indicating a business environment. The organization here can be replaced with a word that covers the environment in which Twitter is being used. Therefore, we choose to replace the word ‘organization’ by ‘social environment’ to make this item suitable for this research.

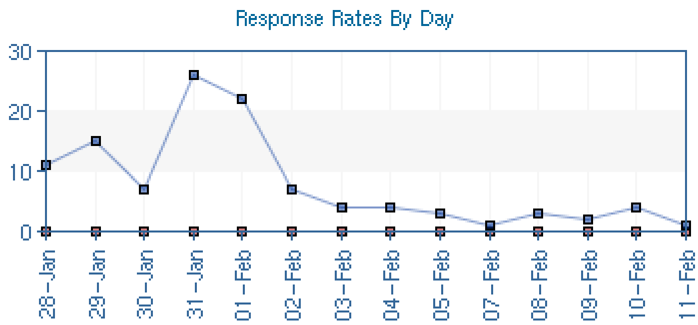
4 Descriptive Statistics and Model validation

This section will analyze the results of the research. We start with some descriptive statistics of our subjects. The software we used for our data analysis was SurveyGizmo and SPSS 17. SurveyGizmo provided us with some statistics on the data collection process. The actual analysis we have done was conducted by using version 17 of SPSS. Then we describe in this chapter how we have prepared our raw data in order to conduct data analyses.

4.1 Data Collection process

We used a free student account on SurveyGizmo.com in order to publish an online survey for our subjects. Then we started collecting data via social networks such as LinkedIn, Facebook and Twitter. We collected the data from January 28th 2010 until February 11th 2010. SurveyGizmo was able to show us a graph on the response rates per day over that period:

Figure 13; The number of completely filled out surveys per day



We sent out the messages over Facebook and LinkedIn on January 28th, January 29th and the 30th. We see that most of our completed surveys were filled out during or straight after that period. The following responses we got mainly from sending Tweets over the Twitter network with the hastags '#daretoask' and '#durftevragen'.

SurveyGizmo.com also distinguishes between complete surveys and abandoned surveys. This way, you can see the rate of people who actually complete the survey against the people who 'just visit' the survey page. During the collection period, 109 people filled out the survey completely, 498 people visited the survey page without filling it out. This means that 21,9% of people who visited the survey page, actually filled it out completely.

Another interesting graph the SurveyGizmo.com application could show us, was where the responses were filled out geographically. The application registers the IP-addresses from computers that were used to fill out the survey and is able to trace the geographical location of that response:

Figure 14; The geographical locations of the responses

Here we see that the biggest dot is in the Netherlands and there are a few dots from different corners in the world. We see a dot in Colombia, America, the UK, Scandinavia and a few dots in South-east Asia.

4.2 Preparing the data for analysis

After downloading a .csv file from SurveyGizmo with all the raw data, we used SPSS to process the data in order to conduct analyses on the data. Firstly, we renamed some variables that were produced by the SurveyGizmo application into shorter, more comprehensive terms. For example, the names of the item-variables were the actual questions. This was such a long string that it made the SPSS document look incomprehensible. We adjusted these variable names into PE1, PE2, EE1, EE2, etc.

The second action we took in order to prepare the data was calculating the opposite values for FC3, or 'PBC5: Twitter is not compatible with other online systems I use.' This question was a reverse question, so we let SPSS recode the values the other way around (7=1, 6=2, 5=3 etc.) into the same variable. The algorithm we used was adding 1 to the maximum value of the score (in this case 7) so we got 8. Then we subtracted the given scores from 8. This way, a score of 7 becomes (8-7) = 1. A score of 6 becomes (8-6) = 2, etc.

4.3 Subject statistics; Gender, Age and Experience

In this research, a total of 109 people filled out the online survey (N=109). Of this population, 26 females (23,9%) and 83 males (76,1) were counted.

4.3.1 Gender

Table 1: Gender Descriptives

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	26	23,9	23,9	23,9
	Male	83	76,1	76,1	100,0
	Total	109	100,0	100,0	

4.3.2 Age

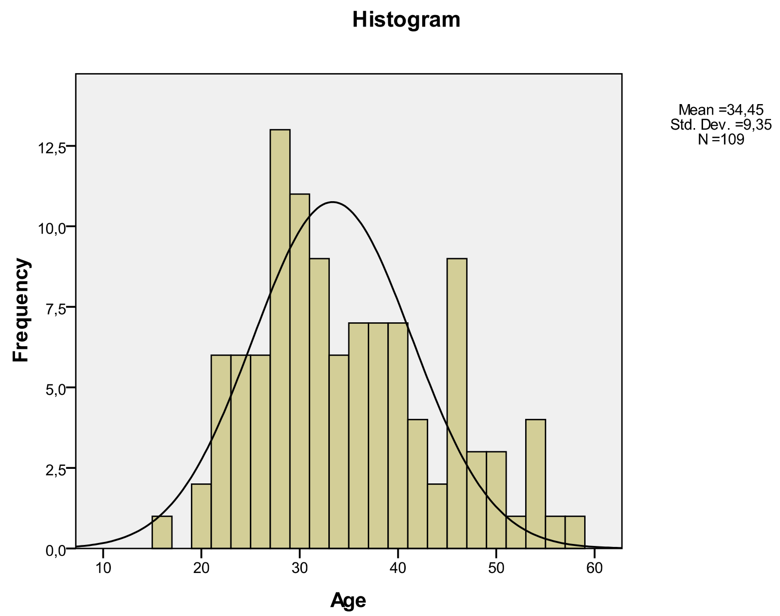
In the population, the Age ranged from 16 to 57 and the average Age was 34,45 years old.

Table 2: Age Descriptives

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Age	109	41	16	57	34,45	9,350

A histogram shows us how the Age in the population is divided:

Figure 15; The Age Histogram



In this histogram, we see that most people from the population are from the age around 30 years old. Also, there is a remarkable peak from people in their mid 40's. Overall, there is a 'clock form' observable which suggests that the population of this research approaches a normal distribution in terms of Age, with a small emphasis on the left.

4.3.3 Experience

In the population, 4 people (3,7%) said they were highly inexperienced. 19 people (17,4%) reported that they were somewhat inexperienced, 16 people (14,7%) reported to be neither inexperienced, nor experienced, the majority of 53 people (48,6%) said they were somewhat experienced and 17 out of the 105 people (15,6%) said they were highly experienced with the use of Twitter.

Table 3: Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 – Highly inexperienced	4	3,7	3,7	3,7
	2 – Somewhat inexperienced	19	17,4	17,4	21,1
	3 – Neither experienced nor inexperienced	16	14,7	14,7	35,8
	4 – Somewhat experienced	53	48,6	48,6	84,4
	5 – Highly experienced	17	15,6	15,6	100,0
	Total	109	100,0	100,0	

4.4 Reasons for Using Twitter

Previous research (Java, Song et al. 2007) reported that ‘daily chatter’ was the most frequently used reason to use Twitter. In our study, we asked the people how often they use Twitter for the different categories distinguished by Java, Song et. al (Daily chatter, Conversations, Information sharing, News). For each category people could fill out on a scale how often they use Twitter for the particular task. They could choose between ‘Never’, ‘Seldom’, ‘Sometimes’ or ‘Often’. For the detailed results on this question, see Appendix C table 10.1. The next step we took within SPSS was calculating binary values for the use of those categories. Using Twitter for a category seldom, sometimes or often meant a ‘1’, if used never then a ‘0’ was calculated. From here, we could determine in how many cases each category was used or not. With this we could also see in how many cases people who filled out the survey had never used Twitter for any purpose. In the population of this research, the percentage of people who use Twitter (Seldom, Sometimes or Often) was 93,6%. The category which had the highest percentage of users was ‘information sharing’. This is in contrary to the work of Java, Song et. al; they found ‘daily chatter’ to be the most frequently used purpose for using Twitter.

Table 4: The use of Twitter	Frequency	Percent
Use Twitter	102	93,6
Daily Chatter	82	75,2
Conversations	85	78,0
Information Sharing	99	90,8
News	89	81,7

4.5 Internal consistency of constructs

To test whether the proposed constructs (PE, EE, SI, FC and BI) are valid, we conduct an Internal consistency study on the individual items firstly and then on the summated variables who form the constructs of our study. We use the commonly used method of Cronbach's alpha in order to test the items for their reliability. Cronbach's alpha is calculated by the following formula:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum \sigma_i^2}{\sigma_X^2}\right)$$

Firstly, the overall Cronbach's alpha based on Standardized items (which is necessary because Behavioral Intention was measured with 5 point scales, whereas the other items were measured using 7 point Likert scales) was ,889. This reliability is well above the in the literature recommended ,70 (Venkatesh, Morris et al. 2003, Compeau, Higgins 1995). The second step we took was calculating the Cronbach's alpha for each summated score by selecting the individual items for each summated item and let SPSS calculated the individual Cronbach's alpha's:

Table 5: Initial Reliability Statistics

	Cronbach's Alpha	N of Items
Performance Expectancy	,909	4
Effort Expectancy	,887	4
Social Influence	,803	4
Facilitating Conditions	,441	4
Behavioral Intention	,975	3

We see in table 5 that all summated scores had a Cronbach's alpha of well above ,70, except for Facilitating Conditions. The other constructs have Cronbach's alpha's that are high enough to state that these constructs are valid so we leave in the items for those constructs. For Facilitating Conditions however, we are interested to see which individual items are contributing to the internal consistency reliability and which are not. We do this by selecting 'Scale if item deleted' and 'Item' in the 'Descriptives' section of the 'Statistics' option menu in 'Reliability Analysis'. Then we run another reliability test in SPSS:

Table 6: Item-Total Statistics for Facilitating Conditions items

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FC1	14,89	8,062	,431	,162
FC2	14,61	10,093	,389	,266
FC3	15,63	9,420	,212	,413
FC4	17,07	11,661	,036	,573

If we look at the final column of table 6, we see that all scores of 'Cronbach's alpha if Item deleted' are below the overall score of ,441, except for FC4. We decided to drop the item and recalculate the Cronbach's alpha, again with the option to see what happens if we delete even more items:

Table 7: Item-Total Statistics for Facilitating Conditions items

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
FC1	11,23	5,178	,517	,415	,240
FC2	10,94	6,960	,483	,395	,371
FC3	11,97	6,731	,212	,052	,755

Table 7 points out that when FC would be deleted too, the Cronbach's alpha for Facilitating Conditions would be ,755, which is above the ,700 threshold. We decided to drop FC3 as well and continue with 2 items for Facilitating Conditions. Our final internal consistency reliability table then looks like this:

Table 8: Final Reliability Statistics

	Cronbach's Alpha	N of Items

Performance Expectancy	,909	4
Effort Expectancy	,887	4
Social Influence	,803	4
Facilitating Conditions	,755	2
Behavioral Intention	,975	3

4.6 Factor Analysis

Not necessarily to reduce the amount of data, but rather to determine whether the theoretically proposed constructs are actually measured by the items we have in our survey, we conduct a Factor Analysis in SPSS. We expect SPSS to find 5 different factors for the items we give as an input: PE, EE, SI, FC and BI should all have their distinct factors. In order to do so, we let SPSS run a Principal Component Analysis with Varimax rotation, on the items that we have selected after reduction by the reliability analysis done in previous section (FC3 and FC4 are left out). Section 11.3 in Appendix C shows for these items the total variance explained for different distinguished numbers of factors. SPSS recognizes 5 different factors (as we expected) and we see that the total variance explained by these 5 factors is 79,925%. We use varimax rotation in order to produce a Rotated Component Matrix which can be seen in Table 9. The varimax rotation maximizes the sum of variances of the loadings (Boslaugh, Watters 2008) and this reduces the complexity of the components, in order for us to recognize the theoretical constructs represented by the factors more easily.

Table 9: Rotated Component Matrix

	Component				
	1	2	3	4	5
PE1	,786	,252	,174	,233	-,026
PE2	,786	,255	,239	,224	,080
PE3	,820	,203	,073	,262	,046
PE4	,814	,152	,126	,153	,075
EE1	,621	,091	,488	,073	,241
EE2	,167	,084	,807	,142	,240
EE3	,197	-,009	,926	,091	,092
EE4	,152	,032	,932	,088	,079
FC1	,106	,078	,079	,117	,914
FC2	,044	-,106	,395	-,090	,777
SI1	,427	,096	,036	,657	,011
SI2	,398	,034	,123	,721	-,022

SI3	-,017	,042	,069	,819	-,068
SI4	,267	,114	,130	,738	,216
BI1	,259	,932	,018	,026	-,004
BI2	,185	,956	,061	,115	-,023
BI3	,217	,957	,024	,097	,038

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Factor loadings are considered significant with values between -.350 and .350 in previous literature (McDaniel Jr., Gates 2009). We see from Table 9 that Component 1 has 7 items that loaded highly. All of the PE items were loaded very highly (PE1 .786, PE2 .786, PE3 .820 and PE4 .814). An item of Effort Expectancy was also loaded highly (EE1 . 621) and the first two items of Social influence (SI1 .427 and SI2 .398) were loaded with significant values. This means that these items all measure the same construct to some extent. The presence of EE1 in the same factor as the items of PE

The presence of significant loadings for SI1 and SI2 can be explained by the fact that Twitter is a social network, where social interactions are taking place. In that way we argue that people would find the system having more personal benefits if their social environment agrees with the use of it, simply because these people in the social environment form 'fellow' users of the system. However, the significance of SI1 and SI2 are much lower than in Factor 4, so we leave SI1 and SI2 out of Factor 1.

Factor 2 contains only significant loadings for the items of Behavioral Intention. These loadings are highly significant with BI1 .932, BI2 .956 and BI3 .957.

The only significant loadings for Factor 3 that can be seen are on Effort Expectancy Items. As discussed above, the loading for EE1 is significant with .488 but there is a higher loading for this item in Factor 1. The rest of items for Effort Expectancy (EE2 .807, EE3 .926 and EE4 .932) are all highly significant.

The items that load significantly in Factor 4 are only items from the Social Influence construct. Items SI1 and SI2 also have significant loadings on Factor 1, but the loadings on Factor are higher. Therefore, we use Factor 4 significant items for the Social Influence construct.

Finally, Factor 5 contains only 2 significant loadings. The items for Facilitating Conditions FC1 and FC2 are loaded with high significance here with respectively .914 and .777. FC2 has also a significant loading in Factor 3, together with the items for Effort Expectancy. It makes sense that having the necessary knowledge to use Twitter (Facilitating Conditions) will make people perceive the use of Twitter is easier (Effort Expectancy). Item FC2 measures both constructs partly but the highest loading is on Factor 5, where FC1 is also loading highly. Considering this, we take items of Factor 5 to form the construct of Facilitating Conditions.

5 Data Analysis

Now that the dataset is validated and the items of our survey are measuring the constructs we want to test from the theory, we conduct two analyses on the data. Firstly, we calculate the Product-Moment Correlations to see how the constructs of our research model are interacting with each other individually based on our dataset. Secondly, we conduct a multiple regression analysis to see how all constructs are interacting with one another in the entire model. All analyses are conducted in SPSS 17 with the reduced dataset by leaving out the FC3 and FC4 items.

5.1 Product-Moment Correlations

To calculate the correlation between the summed scores of each construct, we calculate Pearson's Product-Moment Correlation Coefficient. The formula for Pearson's Product-Moment Correlation Coefficient is (Boslaugh, Watters 2008):

$$r = \frac{\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{s_x}\right)\left(\frac{y_i - \bar{y}}{s_y}\right)}{n-1}$$

In SPSS, we conduct a bivariate correlation test with the checkmark on 'Pearson'. We enter the summated variables PE, EE, SI, FC and BI as well as the variables Age, Gender and Experience into the variables box:

Table 10: Pearson Correlations

		PE	EE	SI	FC	BI	Age	Gender	Exp
PE	Pearson Correlation	1							
	Sig. (2-tailed)								
EE	Pearson Correlation	,507**	1						
	Sig. (2-tailed)	,000							
SI	Pearson Correlation	,562**	,330**	1					
	Sig. (2-tailed)	,000	,000						
FC	Pearson Correlation	,212*	,498**	,134**	1				
	Sig. (2-tailed)	,027	,000	,010					
BI	Pearson Correlation	,469**	,206*	,251**	,078	1			
	Sig. (2-tailed)	,000	,032	,008	,423				
Age	Pearson Correlation	,158	-,126	,015	-,071	,054	1		
	Sig. (2-tailed)	,101	,190	,876	,464	,578			

Gender	Pearson Correlation	,145	-,014	,100	-,025	-,023	,056	1	
	Sig. (2-tailed)	,132	,884	,302	,794	,810	,561		
Exp	Pearson Correlation	,424**	,483**	,257**	,260**	,400**	-,034	-,087	1
	Sig. (2-tailed)	,000	,000	,007	,006	,000	,723	,366	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

This measure tells us an indication of the strength and the direction of the relationship between the individual constructs (Boslaugh, Watters 2008) and variables. Absolute values of Pearson Correlations of between .1 and .29 are considered weak, between .3 and .49 are considered medium and above an absolute value of .5 correlations are considered strong. We also distinguish between two levels of significance. Fore significance levels below .001, we say that the relationship has high significance, for significance levels between .001 and .005 we say that the relationship has low significance. In table 10 we see the results of the Pearson correlation coefficients for our dataset.

5.1.1 The predictors of Behavioral Íntention

We can see that PE has significant correlations with all other constructs except for the moderating variables Age and Gender. The correlation with EE is with .507 and a significance of .000 considered as a strong correlation with high significance. The correlation with SI of .562 and a significance of .000 is also considered a strong correlation with high significance. We find a medium correlation between PE and FC of .212 and with a significance of .027 which is still under the .05 level, this correlation can still be considered significant. The correlation between PE and BI is highly significant (.000) and with positive coefficient of .469 this correlation is medium. This significant relationship confirms our first hypothesis, that there is a positive influence of Performance Expectancy on Behavioural Intention.

H1: Performance Expectancy will have a positive influence on Behavioral Intention to use Twitter is therefore ***accepted.***

Finally, the correlation between Performance expectancy and Experience was significant and had a positive coefficient of .424. No significant relationships were found between the moderators Age and

EE also has significant positive correlations with all other constructs except for Age and Gender. The correlation between EE and SI was with a positive coefficient of .330 and a a significance of .000 a medium correlation. EE also had a significant (.000) correlation of .498 with FC which is a medium correlation. The correlation between EE and BI was weak with .206 and significant with a .032 level significance.

H2: Effort Expectancy will have a positive influence on Behavioral Intention to use Twitter is therefore ***accepted.***

As with Performance Expectancy, EE had no significant relationships with moderators Age and Gender, but there was a significant relationship between EE and Experience. The coefficient here was .483 and the significance level .000. This relationship can be seen as a medium correlation.

Social Influence had besides the relationships described above, significant correlations with FC, BI and Experience. The correlation with FC was .134 and had a significance of .010 and can thereby be typified as a weak but significant correlation. The correlation between SI and BI was with a coefficient of .251 a medium correlation and with a significance level of .008 a significant relation.

H3: Social Influence will have a positive influence on Behavioral Intention to use Twitter is therefore ***accepted.***

Also, there was a medium correlation between SI and Experience of .257 and with a significance level of .007 this relationship was significant.

The only not aforementioned significant relationship of Facilitating Conditions with any other variable was with Experience. With a coefficient of .260 and a significance level of .006 this relationship can be typified as medium with high significance. There was no significant relationship between FC and BI.

H4: Facilitating Conditions will ***not*** *have an influence on Behavioral Intention to use Twitter is therefore* ***accepted.***

As described above, Age and Gender do not have significant correlations with any other construct. Experience however, has strong correlations with all constructs except for Age and Gender. The correlation coefficients are all positive and their significance levels are all < 0.01. This also means that Experience has a direct influence on Behavioral Intention; so it is not a moderator but a predicting variable!

5.2 Testing for moderating effects

The previous section pointed out that Experience has a direct influence on BI and Age and Gender do not have such a relationship. We are still interested in the effects that these variables have on the relationships between our constructs. The UTAUT model assumes that there are moderating effects from Age and Gender.

5.2.1 The moderating effect of Gender

In order to test whether there is a moderating effect going from Age to the relationships between the constructs PE, EE, SI and BI, we conduct linear regressions with SPSS. In this case, with a dichotomous moderating variable and the independent variable being continuous, it is almost always preferable to measure the effect of the independent variable by unstandardized regression coefficients (Baron, Kenny 1986). Firstly, we select all cases where Gender=0 (Male). The second regression will be conducted for all cases were Gender=1 (Female). Then we compare the unstandardized regression coefficients.

Table 11: Regression Coefficients Dependent Variable BI for Male (Gender=0)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,449	,971		2,522	,014
	Performance_Expectancy	,661	,135	,632	4,889	,000
	Effort_Expectancy	-,104	,155	-,080	-,671	,504
	Social_Influence	-,166	,160	-,121	-1,038	,302

Table 12: Regression Coefficients Dependent Variable BI for Female (Gender=1)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,421	1,364		1,042	,309
	Performance_Expectancy	,229	,258	,230	,887	,385
	Effort_Expectancy	,054	,338	,050	,160	,874
	Social_Influence	,255	,264	,233	,966	,345

When comparing these two tables above, we are not necessarily interested in whether the relationships are significant in both cases, but rather in the differences between the unstandardized coefficients (the interactions). Also, this research is not concerned with underlying psychological explanations for the moderating effects; we only test our data on the existence of moderating effects.

We see that for men, the regression coefficient is much higher for Performance Expectancy (.661) than for women (.229). This means that the effect from Performance Expectancy on Behavioral Intention is stronger for men. This is in accordance to what (Venkatesh, Morris et al. 2003) have found in their research.

The unstandardized regression coefficients for Effort Expectancy for men was (-.104) and for women it was higher with (.054). This means that the effect of EE on BI is stronger for women and this again is the same as what (Venkatesh, Morris et al. 2003) have found in their work.

The regression coefficient of Social Influence is again higher for women (.255) than for men (-.166). This means that the effect is stronger for women. Again, this is also found by (Venkatesh, Morris et al. 2003) in their research.

5.2.2 The modearating effect of Age

In order for us to test the moderating effect of Age, we firstly calculate the centered scores of Age and our Independent Variables. We do this in order to reduce the likelihood of having problems with multicollinearity (Baron, Kenny 1986). We calculate the centered variables by subtracting the mean of the particular variable from all individual scores so that the new mean of these centered scores is 0.

Table 13: Descriptive Statistics for the Centered variables

	N	Minimum	Maximum	Mean	Std. Deviation
Age_CENTERED	109	-18,45	22,55	,0000	9,34967
PE_CENTERED	109	-3,70	2,30	,0000	1,59214
EE_CENTERED	109	-4,51	1,49	,0000	1,31138
SI_CENTERED	109	-2,14	2,86	,0000	1,26949
Valid N (listwise)	109				

Then, to test whether Age has a moderating effect, we calculate the interaction variable by multiplying the centered scores of the Independent Variable and Moderator. In formula form, the equation is as follows:

$$Y = \beta + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 (X_1 * X_2) + e_{i,}$$

Where Y is the dependent variable (in our case BI), β is the intercept, X_1 is the independent variable (PE, EE or SI), X_2 is the moderating variable (Gender), the 4th term is the interaction term and the α's are the coefficients. Finally, e_i is the error term. With these terms calculated, we conduct linear regressions to find out the effects of Age on the other relationships.

Table 14: The moderating effect of Age on Performance Expectancy

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,825	,140		27,293	,000
	Age_CENTERED	-,005	,015	-,026	-,300	,765
	PE_CENTERED	,484	,089	,473	5,462	,000
	AGE * PE	-,011	,009	-,109	-1,278	,204

a. Dependent Variable: Behavioral_Intention

Table 15: The moderating effect of Age on Effort Expectancy

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,792	,155		24,454	,000
	Age_CENTERED	,012	,017	,071	,715	,476
	EE_CENTERED	,282	,125	,227	2,252	,026
	AGE * EE	-,004	,011	-,038	-,358	,721

a. Dependent Variable: Behavioral_Intention

Table 16: The moderating effect of Age on Social Influence

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,800	,153		24,891	,000
	Age_CENTERED	,008	,016	,049	,516	,607
	SI_CENTERED	,328	,121	,256	2,704	,008

AGE * SI	-,009	,014	-,060	-,633	,528

a. Dependent Variable: Behavioral_Intention

As we can see in Table 14, 15 and 16 is that firstly, the 'main effects' of PE, EE and SI are still significant on BI. Age however, has no significant main effect in all three tables. Also, there is no significant interaction term in the tables. Therefore, there is no moderating effect of Age on the relationships between BI and our Independent variables.

5.3 Regression Analysis with BI as dependent variable

Now that we have determined the correlations between the individual constructs, we know the crude effects of these constructs on the dependent variable, BI. To get a more thorough understanding of the relationships between the various constructs of our research model in its entirety, we use linear regression analysis. Hereby we investigate the interaction between the independent variables (PE, EE, SI, FC and BI) as well as the associations between those independent variables and the dependent variable, BI. Also, we add the moderators Age, Gender and Experience in the models to see their effects. Like (Carlsson, Carlsson et al. 2006) have done with their research, we use multiple linear regression first to determine the interactions between the variables in the model. Then we use another multiple linear regression to test the relationships between BI and actual usage of Twitter.

5.3.1 ANOVA analysis of the Model

Firstly, we conduct an Analysis of Variances, or ANOVA. ANOVA analysis is used to examine the statistical significance of the correlations between the independent variables (PE,EE, SI, FC) and the dependent variable (BI). We let SPSS run a linear regression.

Table 17: Model Summary without Experience

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,471[a]	,222	,192	1,46405

a. Predictors: (Constant), Facilitating_Cond_2, Social_Influence, Effort_Expectancy, Performance_Expectancy

Table 18: ANOVA[b] without Experience

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	63,530	4	15,882	7,410	,000[a]
	Residual	222,919	104	2,143		
	Total	286,449	108			

a. Predictors: (Constant), Facilitating_Cond_2, Social_Influence, Effort_Expectancy, Performance_Expectancy

b. Dependent Variable: Behavioral_Intention

Firstly, Table 11 shows us that the whole model has an Adjusted R Square of .192. This means the model with all independent variables included, explains 19,2% of the variance in the dependent variable, BI. The higher the R Square value, the better the model is able to explain the factor Behavioral Intention. Table 12 shows that the model is also Significant with a level of .000 which means that the explained variance in BI by the independent variables has a nearly perfect chance of being true.

We have seen in the previous section that Experience in our model is not a moderator, but a predicting variable (just as PE, EE, SI and FC are). So we decide to involve Experience in the rest of this regression analysis as a independent variable. We make a new Model Summary by adding Experience to the Independent Variable box in SPSS Linear Regression:

Table 19: Model Summary with Experience

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,534[a]	,285	,250	1,41048

a. Predictors: (Constant), Experience, Social_Influence, Facilitating_Cond_2, Performance_Expectancy, Effort_Expectancy

Table 20: ANOVA[b] with Experience

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	81,534	5	16,307	8,197	,000[a]
	Residual	204,914	103	1,989		
	Total	286,449	108			

a. Predictors: (Constant), Experience, Social_Influence, Facilitating_Cond_2, Performance_Expectancy, Effort_Expectancy

b. Dependent Variable: Behavioral_Intention

In Table 13 we can see that the R Square of our model where Experience is added as an independent variable has gone up to 25%. Table 14 shows that the significance with adding Experience is still very high; .000.

5.3.2 The determinants of Behavioral Íntention with addition of other Independent variables

We use linear regression to explore the interactions between the dependent variable BI and the independent variables PE, EE, SI and FC. Formally, multiple linear regression formulas take the following form:

$$Y = \beta + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_n X_n$$

Where Y is the dependent variable, the β is the intercept, $X_1, X_{2,\ldots} X_n$ are the independent variables and $\alpha_1, \alpha_{2,\ldots}$ α_n are the coefficients of the independent variables. The first step of this section is to examine the coefficients of the constructs in the model with their significance levels. Table 15 shows these coefficients.

Table 21: Coefficients[a] with Experience

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,297	,748		1,733	,086
	Performance_Expectancy	,438	,116	,428	3,783	,000
	Effort_Expectancy	-,172	,142	-,139	-1,214	,228
	Social_Influence	-,022	,130	-,017	-,168	,867
	Facilitating_Cond_2	-,023	,121	-,018	-,191	,849
	Experience	,450	,150	,295	3,008	,003

a. Dependent Variable: Behavioral_Intention

Here we can see that if we look at the entire model, the only constructs that have a significant influence on Behavioral Intention are Performance Expectancy (Beta = .428 and p-value = .000) and Experience (Beta = .295 and p-value = .003). Both relationships have medium influence with high significance. The other independent variables do not have a significant influence.

H1: Performance Expectancy will have a positive influence on Behavioral Intention to use Twitter is therefore ***accepted.***

H2: Effort Expectancy will have a positive influence on Behavioral Intention to use Twitter is therefore ***rejected.***

H3: Social Influence will have a positive influence on Behavioral Intention to use Twitter is therefore ***rejected.***

H4: Facilitating Conditions will ***not*** *have an influence on Behavioral Intention to use Twitter is therefore* ***accepted.***

5.4 Regression Analysis with Usage as dependent variable

5.4.1 The influence of BI on actual Usage

The first relationship we test is the relationship between Behavioral Intention and the actual usage. Actual usage was measured on the four different categories Twitter is used for according to (Java, Song et al. 2007). These categories are 'Daily Chatter', 'Conversations', 'Sharing Information / URL's' and 'Reporting News'. Values of these categories were ranging on a scale from 0 (highly inexperienced) to 4 (highly experienced). In order to test the relationship between BI and Usage, we have 5 ordinal variables with which we let SPSS run linear regressions:

Table 22: Coefficients of Independent variable BI with usage variables as dependents

Dependent Variable BI		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
Daily Chat	*Behavioral_Intention*	,308	,085	,331	3,625	,000
Conversations	*Behavioral_Intention*	,338	,076	,396	4,468	,000
Sharing Information	*Behavioral_Intention*	,270	,064	,377	4,213	,000
Reporting News	*Behavioral_Intention*	,222	,080	,260	2,783	,006

In Table 16 above we see that Behavioral Intention had a significant positive effect on all types of use.

H6: Behavioral Intention will have a positive influence on the actual Usage of Twitter is therefore ***accepted.***

5.4.2 Testing the relationship between Facilitating Conditions and actual usage

Facilitating Conditions, or 'the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system' is being hypothesized in our research model to have a direct influence on the actual Usage. We have seen in section 5.1.1 that Facilitating Conditions did not have a significant relationship with Behavioral Intention. Now we use linear regression again to see whether FC has a direct effect on usage. The ordinal variable Facilitating Conditions (the summated variable consisting of 2 items; FC1 and FC2) is put into the SPSS linear regression with the dependent variables of Daily Chat, Conversations, Sharing Information and Reporting News.

Table 23: Coefficients of Independent variable FC with usage variables as dependents

Dependent Variable FC		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
Daily Chat	Facilitating_Cond_2	,102	,113	,087	,901	,370
Conversations	Facilitating_Cond_2	,093	,103	,087	,904	,368
Sharing Information	Facilitating_Cond_2	,223	,084	,248	2,653	,009
Reporting News	Facilitating_Cond_2	,128	,103	,120	1,246	,215

With a Beta of .248 and a level of significance of .009, Sharing Information is the only category of usage that had a positive direct influence from FC that is significant. The other categories did not have significant relationships with FC.

H5: Facilitating Conditions will have a positive direct influence on the Usage of Twitter, is therefore ***partially accepted.*** *Only in the case of 'Sharing Information', Facilitating Conditions have a direct positive influence on the Usage of Twitter.*

5.4.3 Testing for Moderating effects of Age and Experience

To test all of our proposed relationships in our model, we will test the moderating effects that Age and Experience could have on the relationship between Facilitating Conditions and Usage. We calculate the centered scores for these variables and use linear regression in order to find the effects. We use 'Sharing information' as dependent variable here, as we have found that this is the only type of usage that has a significant relationship with Facilitating Conditions.

Table 24: The effects of Experience on FC – Usage (Sharing information)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,066	,103		29,770	,000
	FC_CENTERED	,107	,085	,119	1,261	,210

	EXP_CENTEREd	,412	,099	,377	4,157	,000
	EXP * FC	-,058	,060	-,090	-,960	,339

a. Dependent Variable: Sharing_info

Table 25: The effects of Age on FC – Usage (Sharing information)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,050	,110		27,805	,000
	FC_CENTERED	,064	,298	,071	,213	,832
	Age_CENTERED	,005	,012	,038	,394	,694
	AGE * FC	,005	,008	,188	,566	,572

a. Dependent Variable: Sharing_info

We see from the tables above that Age and Experience do not affect the relationship between Facilitating Conditions and the use of Twitter significantly. The Significance scores of ,339 and ,572 are way higher than the significance level of ,05. These insignificant relationships are in contrary to what has been suggested in the original UTAUT model (Venkatesh, Morris et al. 2003).

5.5 Summary

In this Chapter, we have conducted several analyses on our dataset to test the interactions and relationships between the variables. Hereby we found with the Product-Moment correlations test that Performance Expectancy, Effort Expectancy and Social Influence all had a significant positive correlation with Behavioral Intention. Facilitating Conditions however, did not have a significant relationship with Behavioral Intention. Another relationship that proved to be significant was the relationship between Experience and Behavioral Intention. Rather than having a moderating influence, Experience was found to be one of the predictors of Behavioral Intention.

Then we investigated the moderating effects of Gender and Age. Gender was proven to have a moderating effect in such a way that the effect of Performance Expectancy on Behavioral Intention was greater for men, the effect of Effort Expectancy on Behavioral Intention was greater for women and the effect of Social Influence on Behavioral Intention was greater for women. Age was found not to have a significant moderating effect on the other relationships.

Incorporating Experience in the model as an Independent Variable and a predictor of Behavioral Intention, we conducted a multiple linear regression analysis. When looking at the whole model, only Performance Expectancy and Experience were found to have significant regression coefficients on Behavioral Intention. Despite the crude significant effects that Effort Expectancy and Social Influence had on Behavioral Intention, these effects became insignificant when incorporating all independent variables in the model. Facilitating Conditions also was found to have an insignificant relationship with Behavioral Intention, as was hypothesized.

We further investigated Facilitating Conditions and its relationship on the actual Usage. We used the four categories of usage found by (Java, Song et al. 2007) and analyzed how Behavioral Intention and Facilitating Conditions were related to these variables. All four categories showed significant positive relationships with Behavioral Intention. Facilitating Conditions however, was only found to have a significant relationship with the actual usage of Twitter in the context of 'Information Sharing', which was earlier found to be the category that Twitter is being used for mostly. The other categories of use showed no significant relationships with Facilitating Conditions.

The table below shows the hypotheses of this research and their results from Data analyses:

Table 26: Summary of Hypothesis findings

Hypothesis	Construct	Product-Moment	Regression
H1	PE → BI	Accepted	Accepted
H2	EE → BI	Accepted	Rejected
H3	SI → BI	Accepted	Rejected
H4	FC ≠ BI	Accepted	Accepted
H5	FC –> Usage	N/A	Partly Accepted
H6	BI → Usage	N/A	Accepted

6 Discussion

In this chapter we will discuss the results found in the previous chapter. We will discuss several possible implications of the results and secondly, we will discuss the limitations of our study.

In our research, the category of usage defined by (Java, Song et al. 2007) that was found to be representing the mostly used purpose of using Twitter, was ‘Sharing Information’, where in their research, ‘Daily Chatter’ was the main purpose of most users. It may be that Twitter’s functionality has shifted over the last few years. It is not unlikely to think that ‘Daily chatter’ is merely a function that suits best with instant messenger programs such as MSN or online social networks such as Facebook or Hyves. Sharing information / URL’s on Twitter is also a function that is made easier with online applications such as bit.ly. Bit.ly creates very short links from url’s that take a lot of characters. Also our survey, which had the original link of http://app.sgizmo.com/s/survey_slug.php?sg_id=234351&sg_slug=the-success-story-of-twitter, was translated by bit.ly into ‘bit.ly/9F5228’. This link was more appropriate to post in a Tweet online since it did not take up as much of our 160 characters as the original link. Many tweets seen on Twitter use these shortened links in order to place URL’s on Twitter.

Performance Expectancy, i.e. the gained benefits by using Twitter, had a significant positive effect on the Behavioral Intention to use Twitter. It had a significant crude effect and when other independent variables (EE, SI, FC) were added to the model, the coefficient of determination did not change considerably. The effect was shown to be moderated by Gender in such a way that the effect was stronger for men. Age was not affecting the relationship, in contrary to what UTAUT was assuming. The subjects of our study found that using Twitter will give you a social boost, it will enable you to communicate online more quickly and it will be useful for your interpersonal communication. The functionality of uploading tweets even with your mobile phone enables people to share anything that can be formulated within 160 characters quickly, to anyone who are interested. The daily news in the Netherlands even mentioned that during the regional elections, several political leaders posted tweets about what they were doing with their cell phones. They might agree with the subjects of our research that using Twitter enables to communicate online more quickly.

Despite the crude significant effects found with Effort Expectancy and Social Influence, their significance disappeared when tested the model as a whole. Apparently, how easy to use Twitter and what others think of using Twitter is important in explaining why people intend to use Twitter, but not significantly important when looking at the whole picture. We hypothesized that Facilitating Conditions has no influence on Behavioral Influence and the lack of significance in the relationship between these two factors show that this is true. Not even the crude effect of FC on BI showed a significant relationship. Adding other independent variables did not show any significant relationship either. The relationship with usage was tested and found to be significant between Facilitating Conditions and Usage in the context of Sharing Information / URL's, again the most frequently used category for usage. Being the most frequently used category of Usage and having significance with Facilitating Conditions is important, because it shows that for the most important reason to use Twitter, having the knowledge and skills necessary for using Twitter has a positive influence on this Usage. For example, it would be less interesting if this relationship was found to be true only for a category of usage that is not as important, such as 'Conversation'.

Being experienced with the use of Twitter has a direct significant and positive influence on the intention to use it again. This implies that the use of Twitter must have some benefits in the perception of its users, otherwise these users would not intend to use it again. Where we expected Experience to have a moderating role in the model, it appeared from our data to have a direct influence on Behavioral Intention. The relationships between Experience and other constructs also showed that the more experience someone has with the use of Twitter, the more benefits he or she perceives the use of Twitter has, the easier he or she perceives the usage will be and the more important it becomes whether important other people think he or she should use Twitter.

6.1 Limitations of this study

Even though the R square of our model was .285, the results from this research should be interpreted cautiously. The Product-Moment matrix shows that there was some multicollinearity between the constructs and this might reduce the interpretability of the data (Boslaugh, Watters 2008). Also, with N=109, the population of this study was still very small compared to the overall number of Twitter users and therefore should be interpreted cautiously. Also, when looking at the population of this study, we must say that most of the Twitter users were located in the Netherlands.

7 Conclusions

In this chapter, we will provide an answer to our research question and make some recommendations for future research.

7.1 Answering the research question

Firstly we will provide an answer to our main research question. The research question was:

What are the success factors behind the success in acceptance of the Web 2.0 application Twitter?

This research has investigated several psychological constructs and their relationships with the usage of Twitter. We have formulated some hypotheses and tested them with several statistical methods. Thereby we have found that Performance Expectancy i.e. the gained benefits by using Twitter', has a medium but significant influence on the intention to use Twitter. Effort Expectancy and Social Influence have crude significant effects on the intention to use Twitter, but when we look at all psychological constructs at the same time in a model these effects were shown to be insignificant. Facilitating Conditions was found to have a positive and significant influence on the most important category of Twitter usage in our research, 'Sharing Information / URL's'. Experience in using Twitter also showed to be a significant and positive predictor of the Intention to use Twitter.

Age did not have any moderating effect on the constructs as was suggested by UTAUT, but Gender was shown to moderate between Performance Expectancy, Effort Expectancy, Social Influence their relationships with Behavioral Intention. The relationship between Performance Expectancy and Behavioral Intention was stronger for particularly men, the relationship between Effort Expectancy and Behavioral Intention was stronger for particularly women and finally, the relationship between Social Influence and Behavioral Intention was stronger for particularly women.

When we reflect this conclusion on our literature study, we conclude that just as in many other technology acceptance studies (Carlsson, Carlsson et al. 2006)(Venkatesh, Morris et al. 2003) amongst others, Performance Expectancy is the strongest predictor in explaining the intention to use Web 2.0 application Twitter. Where Effort Expectancy and Social Influence were found to be significantly strong predictors of Behavioral Intention too, we have only found their crude effects to be significant. Facilitating Conditions was shown to have significant relationship with the most frequently used category of Use, "Sharing information / URL's", but not with Intention to use as was also hypothesized.

7.2 Implications

Even though it is important for managers and designers of Web 2.0 applications to take into account Effort Expectancy and Social Influence, the emphasis when designing micro-blogging services on the Internet should be on Performance Expectancy. This research has shown that Performance Expectancy was the UTAUT construct that had the most significant influence on the intention to use Twitter. Designers should therefore focus on how new applications are bringing expected benefits for the users. This consideration is even more important when developing new Web 2.0 applications of which it is expected to be adopted merely by men rather than by women.

Despite the significant importance of Performance Expectancy however, Effort Expectancy and Social Influence must still be taken into consideration when designing a new application like Twitter. Also, Facilitating Conditions must be provided in order for people to use the application. Apart from these factors to take into consideration, designers should find a way to let their users get Experience with their applications as quickly as possible. This research has shown that Experience with using a application will have a direct positive effect on the intention to use it again.

7.3 Recommendations for future research

Future Research can be conducted on Twitter with bigger samples of Twitter users spread around the globe. The population of this study was mainly concentrated in the Netherlands and it could be interesting to see what results this research would have with populations from different areas in the world. Also, other statistical approaches could be considered such as Structural Equation Modeling. Partial Least Squares is a technique that is being used in the original work of (Venkatesh, Morris et al. 2003) and could be used to extend the results of this research. Also, we used linear regression for testing the relationships between actual usage and other constructs; we did this because we had ordinal variables of each category of usage (ranging from 0 – never use to 3 – often use). Future research could consider to use other statistical methods to analyze this data. (Carlsson, Carlsson et al. 2006) for example used logistic regression for testing these relationships. Thereby they distinguished between use and non-use (dichotomous variables) rather than an ordinal variable to do so.

Finally, Experience was measured by asking 1 item about how experienced the user was with using Twitter. This is a limitation of this study because experience could also be interpreted as ‘overall experience’ with the internet, or other social applications for example. Future research could investigate the relationship between overall experience and the intention to use Twitter more thoroughly.

8 Appendix A – Theory Overview

Overview of the used Acceptance models and theories in order to formulate UTAUT (Venkatesh, Morris et al. 2003):

Theory or Model	Core Constructs	Reference(s)
Theory of Reasoned Action (TRA)	▪ Attitude Toward Behavior ▪ Subjective Norm	(Fishbein, Ajzen 1975, Ajzen, Fishbein 1980)
Technology Acceptance Model (TAM)/(TAM2)	▪ Perceived Usefulness ▪ Perceived Ease of Use ▪ Subjective Norm (TAM2 only)	(Davis, Bagozzi et al. 1989, Davis 1989)
Motivational Model (MM)	▪ Extrinsic Motivation ▪ Intrinsic Motivation	(Davis 1992)
Theory of Planned Behavior (TPB)	▪ Attitude Toward Behavior ▪ Subjective Norm ▪ Perceived Behavioral Control	(Ajzen 1991)
Combined TAM and TPB (C-TAM-TPB)	▪ Attitude Toward Behavior ▪ Subjective Norm ▪ Perceived Behavioral Control ▪ Perceived Usefulness	(Taylor, Todd 1995)
Model of PC Utilization (MPCU)	▪ Job-fit ▪ Complexity ▪ Long-term Concequences ▪ Affect Toward Use ▪ Social Factors ▪ Facilitating Conditions	(Thompson, Higgins et al. 1991)
Innovation Diffusion Theory (IDT)	▪ Relative Advantage ▪ Ease of Use ▪ Image ▪ Visibility ▪ Compatibility ▪ Results Demonstrability ▪ Voluntariness of Use	(Rogers 1995, Moore, Benbasat 1991)
Social Cognitive Theory (SCT)	▪ Outcome Expectations—Performance ▪ Outcome Expectations—Personal ▪ Self-Efficacy ▪ Affect ▪ Anxiety	(Compeau, Higgins 1995)

9 Appendix B – The survey

9.1 Items Used in the Survey:

Performance expectancy

U6: I would find Twitter useful for my interpersonal communication.
RA1: Using Twitter enables me to communicate online with others more quickly.
RA5: Using Twitter increases my productivity of communication online.
OE7: If I use Twitter, I will increase my chances of getting a social boost.

Effort expectancy

EOU3: My interaction with Twitter is clear and understandable.
EOU5: It is easy for me to become skillful at using Twitter.
EOU6: I find Twitter easy to use.
EU4: Learning to operate Twitter is easy for me.

Social influence

SN1: People who influence my behavior think that I should use Twitter.
SN2: People who are important to me think that I should use Twitter.
SF1: I use Twitter because of the proportion of friends who use Twitter
SF4: In general, my social environment has supported the use of Twitter.

Facilitating conditions

PBC2: I have the resources necessary to use Twitter.
PBC3: I have the knowledge necessary to use Twitter.
PBC5: Twitter is not compatible with other online systems I use.
FC3: A specific person (or group) is available for assistance with Twitter difficulties.

Behavioral intention to use the system

BI1: I intend to use Twitter in the next month.
B12: I predict I would use Twitter in the next month.
B13: I plan to use Twitter in the next month.

9.2 Survey Invitations

In order to attract people who are familiar with the use of Twitter to fill out our survey, we sent out the following message:

Hi there!

For our research on Twitter, we are looking for Twitter users to fill out our 2-minute survey. Please help us by filling out the survey here:

http://www.surveygizmo.com/s/234351/the-success-story-of-twitter

And feel free to send this link to your Twitter followers as well, we would be very grateful!

Kind regards

10 Appendix C – Statistics

This Appendix contains several tables with Statistics that were found unimportant enough to leave them out of the main text.

10.1 The usage of Twitter

	Never Use	Seldom Use	Sometimes Use	Often Use
Daily Chatter	27 (24,8%)	27 (24,8%)	23 (21,1%)	**32 (29,4%)**
Conversation	24 (22%)	28 (25,7%)	**36 (33%)**	21 (19,3%)
Sharing Information	10 (9,2%)	11 (10,1%)	42 (38,5%)	**46 (42,2%)**
Reporting News	20 (18,3%)	21 (19,3%)	**37 (33,9%)**	31 (28,4%)

10.2 Individual Item Descriptive Statistics

Performance Expectancy

	Mean	Std. Deviation	N
E1	4,75	1,775	109
PE2	5,15	1,820	109
PE3	4,51	1,849	109
PE4	4,40	1,738	109

Effort Expectancy

	Mean	Std. Deviation	N
EE1	5,16	1,578	108
EE2	5,56	1,436	108
EE3	5,70	1,348	108
EE4	5,81	1,377	108

Social Influence

	Mean	Std. Deviation	N
SI1	3,20	1,690	108
SI2	3,06	1,668	108
SI3	2,94	1,515	108
SI4	3,36	1,556	108

Facilitating Conditions

	Mean	Std. Deviation	N
FC1	5,84	1,628	109
FC2	6,13	1,241	109
FC3	5,83	1,035	109
FC4	3,66	1,623	109

Behavioral Intention

	Mean	Std. Deviation	N
BI1	3,83	1,655	109
BI2	3,80	1,660	109
BI3	3,77	1,692	109

10.3 Variance Explained by factors in Principal Component Analysis

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6,526	38,387	38,387	6,526	38,387	38,387	3,620	21,291	21,291
2	2,821	16,593	54,979	2,821	16,593	54,979	2,950	17,354	38,646
3	1,927	11,333	66,313	1,927	11,333	66,313	2,928	17,224	55,870
4	1,176	6,917	73,230	1,176	6,917	73,230	2,452	14,422	70,292
5	1,138	6,695	79,925	1,138	6,695	79,925	1,638	9,633	79,925
6	,861	5,065	84,990						
7	,476	2,803	87,793						
8	,418	2,461	90,254						
9	,394	2,320	92,574						
10	,290	1,706	94,279						
11	,250	1,471	95,751						
12	,197	1,161	96,912						
13	,181	1,066	97,977						
14	,168	,990	98,967						
15	,085	,498	99,466						
16	,070	,409	99,875						
17	,021	,125	100,000						

Extraction Method: Principal Component Analysis.

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