SOCIAL PSYCHOLOGICAL DETERMINANTS OF MOBILE COMMUNICATION TECHNOLOGY USE AND ADOPTION

A COMPARISON OF THREE MODELS TO EXPLAIN AND PREDICT MOBILE COMMUNICATION TECHNOLOGY BEHAVIOR

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"It is utterly implausible that a mathematical formula should make the future known to us, and those who think it can would once have believed in witchcraft" (p. 167).

Bertrand de Jouvenel (1967)

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Contents

Preface

This dissertation focuses on the social psychological determinants of mobile communication technology use and adoption in an attempt to better understand people's behavior for adopting and using innovative information and communication technologies. In particular, this study emphasizes the comparison of three media use models to explain and predict media technology behavior from different theoretical perspectives.

In the year 1954, in one of the first mass communication textbooks, 'The Process and Effects of Mass Communication', Wilbur Schramm posses the question, "What determines which offerings of mass communication will be selected by a given individual?" (p.19). The answer to this question was what Schramm called the 'fraction of selection'. People weigh the level of reward they expect from a given medium or message against how much effort they must make to secure that reward. According to Schramm, individuals make media and content choices based on the expectation of reward and effort required.

Schramm's question in 1954 is still relevant today, perhaps even more relevant as the offers, choices and possibilities of new communication technologies, especially mobile communication technology, are more diverse and dynamic then in the 1950s.

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To Marieke, Hugo, & Boudewijn

1

Social Psychological Determinants of Mobile Communication Technology Use and Adoption

In this chapter, first the context of the study will be presented, followed by an introduction of three social psychological media use models and the theoretical perspectives from which they originated. Next, the scope and research questions of the study will be presented, followed by an overview of the study.

1.1 Context of the Study

With the arrival of wireless communication technologies people are enabled to be accessible at all times and places. The use of mobile communication technology, like the mobile phone, and other personal communication technologies, like the personal digital assistant (PDA) has become almost fully integrated in everyday life for both social and business purposes. The adoption and use of mobile communication technology has increased exponentially in almost similar patterns world-wide (see e.g., Carlson, Kahn, & Rowe, 1999; Crisler, Anneroth, Aftelak, & Pulli, 2003). In a variety of contexts people want to use mobile communication devices to make phone calls, exchange messages with family, friends or co-workers, read and send e-mail, take pictures, listen to music, or want to have access to data files. The mobile phone as the most prominent example of mobile communication technology has become, as Wei (2001) stated, "more than just a talking device on the move" (p. 703). It represents a converged new communication and information technology with a variety of extensive interpersonal and mass communication services such as short message service (SMS), voice-mail, e-mail, Internet access, personal navigation system, video phone, and TV broadcasts. According to Bohlin, Burgelman, and Casal (2007) globally, wireless services, driven by the mobile phone, have advanced faster in the last 10 years than the whole of telecommunications technology over the last 100 years, and the number of mobile phone users has surpassed the number of fixed line subscribers since the year 2000.

The mobile communication industry, including the telecommunications companies and manufacturers are operating in a very competitive market, where a lot of time and money is invested to develop new services and products that meet the demands of a very diverse and demanding group of customers. Annual revenues of the suppliers of equipment and handsets for the mobile industry globally have passed the 100 billion euros mark since a number of years (Bohlin et al., 2007).

Understanding the behavior of mobile communication technology consumers is important for the mobile communication industry in order to be able to react accurately to the changing behavior of their customers. Understanding peoples' needs and desires is vital to be able to offer products and services that consumers will actually use. For both academia and the mobile communication industry the behavior of the mobile consumer is important to gain a better insight in the process of technological innovation, diffusion and use of mobile communication technology (see e.g., Green, Harper, Murtagh, & Cooper, 2001).

Understanding people's behavior for adopting and using innovative information and communication technologies - such as mobile communication technology - is central in this dissertation. In particular, this dissertation focuses on the social psychological determinants of mobile communication technology use and adoption. The research framework of the dissertation is based on psychological research on the origins of goal-directed human behavior. Aarts, Verplanken, and Van Knippenberg (1998) argue that, in general, psychological research on the origins of goal-directed human behavior relies on expectancy-value models of attitudes and decision making, rooted in theories of rational choice.

Information and communication technology use and adoption as a form of goal-directed human behavior is a topic that is central to several distinct bodies of literature, which have yielded many competing media use models to explain and predict media behavior from different research perspectives. In the next paragraph three social psychological media use models stemming from three prominent theoretical perspectives on media behavior will be presented. The theoretical perspective as well as the research focus of each media use model will be discussed in more detail in Chapter 3.

1.2 Media Use Models

One of the first research traditions to focus on media behavior from a user's perspective is the uses and gratifications approach. Stemming from mass communication research, uses and gratifications guides the assessment of people's motivations for media usage and access. In a more general definition of uses and gratifications, Katz, Blumler, and Gurevitch (1974), posit that uses and gratifications research is "concerned with the social and psychological origins of needs, which generate expectations of the mass media or other sources, which lead to differential patterns of media exposure (or engagement in other activities), resulting in need gratifications and other consequences, perhaps mostly unintended ones" (p. 20). To ground uses and gratifications more theoretically several authors (e.g., Galloway & Meek, 1981; Rayburn & Palmgreen, 1984) moved away from the origin of needs perspective and incorporated an expectancy-value perspective as used within social psychology (e.g., Fishbein & Ajzen, 1975) into uses and gratifications research, which lead to the expectancy-value judgments model of uses and gratifications (see e.g., Babrow & Swanson, 1988).

Expectancy-value judgments model of uses and gratifications. According to Palmgreen (1984) the expectancy-value judgments model of uses and gratifications is a process model which states that the products of beliefs (expectations) and evaluations (values) influence the seeking of gratifications, which in turn influence media consumption. Such consumption results in the perception of certain gratifications obtained, which then feed back to reinforce or alter an individual's perceptions of the gratifications-related attributes of a particular medium.

Another example of adapting social psychological theory to understand media technology behavior is the model of media attendance (LaRose & Eastin, 2004) which originated from Bandura's (1986) social cognitive theory. Within social cognitive theory, human behavior is defined as a triadic, dynamic, and reciprocal interaction of personal factors, behavior, and the environment (Bandura, 1986). This triadic causal mechanism is mediated by symbolizing capabilities that transform sensory experiences into cognitive models that guide actions. LaRose and Eastin argue that within social cognitive theory, behavior is an observable act and the performance of behavior is determined, in large part, by the expected outcomes of behavior, expectations formed by our own direct experience (enactive learning) or mediated by vicarious reinforcement observed through others (observational learning).

Model of media attendance. Within the model of media attendance media usage is defined as overt media consumption behavior, and it is determined by the expected outcomes that follow from media consumption, habit strength, self-efficacy, self-regulation, and experience.

From the field of information systems research, technology and information systems scholars have been adapted theories from social psychology to explain media technology behavior, as well. Information systems research studies how and why individuals adopt new information technologies.

Unified model of acceptance and use of technology. In an attempt to integrate the main competing user acceptance models (e.g., theory of reasoned action, technology acceptance model, theory of planned behavior, social cognitive theory, diffusion of innovation theory), Venkatesh, Morris, Davis, and Davis (2003) formulated a unified model of acceptance and use of technology based on the unified theory of acceptance and use of technology. Four constructs in the unified model of acceptance and use of technology play a significant role as direct determinants of user acceptance and usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions.

1.3 Research Questions and Scope

The presented theoretical perspectives to understand media technology use and adoption are each broad bodies of literature with rich research traditions behind them, yet they also converge on the central processes and phenomena related to the formation of users' intentions to use media technology, as part of an extended model of media behavior (cf. Stafford, Stafford, & Schkade, 2004).

In this dissertation the above-mentioned models and their extensions are discussed and both empirically and theoretically compared within the context of mobile communication technology use. The key research questions to be answered in this dissertation are therefore:

RQ1: Which current media use model statistically best explains the use and predicts the adoption of mobile communication technology? (Empirical power)

RQ2: Which current media use model best substantially explains the use and predicts the adoption of mobile communication technology? (Theoretical power)

Although the focus of this dissertation is on the social psychological determinants of mobile communication technology use and adoption, this dissertation is not an attempt to unravel the deeper social psychological meaning of the mobile communication technology itself. This dissertation mainly emphasizes the comparison of three media use models to explain and predict media technology behavior from different theoretical perspectives. Therefore, any media technology could have been used to compare the three media use models and to subsequently answer the two key research questions. Mobile media technology behavior is considered to be an instance of general media technology behavior. Mobile communication technology contains both well-accepted media technologies such as the mobile phone and new innovative media technologies such as mobile video phone, it is therefore a very appropriate media technology to be deployed to compare the media use models in both explaining and predicting media technology behavior (see Chapter 7 for a more detailed description of the mobile phone technologies).

1.4 Overview of the Study

Chapter 2 presents a brief account of the various empirical research approaches that study mobile communication technology use and adoption.

Chapter 3 introduces three theoretical perspectives on the understanding of people's behavior for adopting and using media technology, e.g. the expectancy-value perspective on uses and gratifications, a social cognitive perspective on media technology behavior, and the unified theory of acceptance and use of technology. At the end of the chapter, the convergence between the three perspectives on the central processes and phenomena related to the understanding of media technology behavior is discussed.

Chapter 4 describes in more detail the models and hypotheses that originate from the three theoretical perspectives described in Chapter 3. At the end of the chapter a provisional comparison of the three media use models is presented.

Chapter 5 discusses the criteria to systematically evaluate and compare the three models. On the basis of a selection of the criteria discussed, the three models will be both theoretically and empirically evaluated and compared.

Chapter 6 presents in more detail the structural equation modeling methodology and procedures used in this study. At the end of the chapter, the goodness-of-fit tests and cutoff criteria used in this study to evaluate and compare the three media use models are summarized.

Chapter 7 evaluates and compares the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology in the context of mobile phone use as well as in the context of mobile video phone adoption on the basis of the empirical criteria proposed in chapter 5.

Chapter 8 evaluates and compares the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology in the context of mobile phone use as well as in the context of mobile video phone adoption on the bases of the qualitative criteria proposed in chapter 5.

Chapter 9 presents the conclusions drawn from the findings of both the empirical and theoretical comparison of the three models within the context of mobile communication technology use and adoption.

Chapter 10 discusses the conclusions and implications drawn from the findings of both the empirical and theoretical comparison of the three media use models. Subsequently, the limitations of the study are acknowledged, followed by implications for using empirical models in media use research.

2

Mobile Communication Technology Research

The aim of this chapter is to present a brief account of the various empirical research approaches that study mobile communication technology use and adoption.

2.1 Approaches of Mobile Communication Technology Research

Empirical research studies on mobile communication technology use and adoption can roughly be divided in either a research approach that takes on a more sociological perspective towards mobile communication technology research or a research approach that takes on a more psychological perspective.

Sociological perspective. Research studies that take on a sociological perspective toward mobile communication technology (e.g., Katz, 1999, 2003; Ling, 2004) most often apply qualitative methodologies, such as in-depth interviews and observation to study mobile communication technology use and adoption; for example, Humphreys (2005) examined mobile phone usage from two main perspectives: how social norms of interaction in public spaces change and remain the same; and how mobile phones become markers for social relations and reflect tacit pre-existing power relations. Based upon a year-long observational field study and in-depth interviews, Humphreys suggests that mobile phones do privatize and atomize public spaces as mobile phone users block out others nearby; however, mobile phone users can publicize their private information when they use their mobile phones loudly in public. Mobile phones may allow for greater mediated contact between persons due to their flexibility and mobility, which in turn may lead to an overall collectivizing function in society (p. 828).

Mobile communications technology research from a sociological perspective also includes research approaches such as ethnographic and cultural studies (e.g., Brown, Green, & Harper, 2002; Höflich & Hartmann, 2006). Brown (2002) argues that mobile communication technologies impact how we organize our days and our evenings, how we work, and even how we make friends. Public places now contain private conversations; text messages disturb intimate moments, and the media hails each new cultural/technological development, from "textual-harassment" to "phone envy" (p. 3); for example, the Sussex Technology Group (2001) identified social and cultural issues emerging around the use and ownership of mobile phones at a transitional period in the technology's uptake. The study aimed to locate negotiations which appear in users' perceptions of the mobile phone; for example, negotiations over 'old yuppie' versus 'new normal' usage, or 'public' versus 'private' call-types. Based on forty recorded interviews with locals and visitors to the town of Brighton (UK), who were all using or visibly displaying a mobile phone, it was concluded that the central metaphor that emerged from users' comments was that of space.

The Sussex Technology Group demonstrated that the preoccupation with space and its metaphors certainly occurs at almost every level of mobile use and perception, from public performativity, that is the daily behavior or performance of individuals based on social norms or habits (see e.g., Lloyd, 1999) to private practices in space. The contradictory public-private dimension of the mobile phone use - the manner in which it brings previously 'hidden' aspects of private communication into the visible and public spaces of the street - appeared to produce anxiety in a number of respondents. Embarrassment, inhibition, ostentation and enjoyment are 'structures of feeling' which often accompany mobile phone use. The Sussex Technology Group poses that the focus on space and spatial metaphors, the articulation of many of these issues, is to be expected because the mobile phone disrupts established socially defined boundaries and regulations concerning the use of space. Talking to a lover or even a colleague in the company of strangers can be disconcerting. According to the Sussex Technology Group, new forms of social conduct and regulatory mechanisms (initially at the level of individual conduct, and then also by increasing social sanctions) can be expected to evolve in order to 'contain' the technological challenges to public/private divisions presented by mobile telephony.

The demographic study on loneliness and new technologies in a group of Roman adolescents (Prezza, Pacilli, & Dinelli, 2004) is an example of a quantitative sociological study of mobile communication technology use (see also e.g., Katz & Aakhus, 2002). Prezza et al. explored the relationships among class membership (computer science or not), gender and socio-economic status on the one side and frequency and modality of using the computer, Internet and the mobile phone at the other side. The results of the questionnaire of 311 Italian secondary school students confirmed that those with a higher socio-economic status use Internet more; the computer is used more by those who frequent a computer science section and by those with a higher socio-economic status. At school students could choose between computer science sections (in which traditional programs are integrated with theoretical lessons and a computer science laboratory) and non computer science sections (in which computer science is not studied). Loneliness emerged in correlation to gender (higher in females), but not in correlation to socio-economic status. Moreover it emerged at both the univariate and multivariate level in correlation to the use of Internet and in negative correlation to frequenting an informal peer group. A positive relationship between feelings of loneliness and number of friends who go on-line emerged only at the univariate level. The use of the mobile phone was almost completely independent from the variables examined here.

From a social ethnographic perspective on mobile communication technology, Weilenmann and Larsson (2000) explored how ethnomethodology and conversation analysis can be used to inform the design of new information technology for young people. Weilenmann and Larsson argue that ethnomethodology and conversation analysis, in taking members' own accounts into consideration, provide insight into how teenagers go about producing social order: what it is that they do in order to be teenagers. Weilenmann and Larsson identified three categories of mobile phone use: actual use, young people's conversations on and use of the mobile phone; reported use, young people's conversations about their mobile phone use; and social impact, implications of mobile phone use on the ongoing social context. Weilenmann and Larsson propose that these three categories of mobile phone use are important to distinguish, as they imply different methods for collecting data, and of course, give different types of results.

Psychological perspective. Mobile communications technology research from a psychological perspective is generally concerned with examining people's mobile communication technology behavior in terms of perceptions, expectations and attitudes towards the mobile communication technology; for example, Knutsen (2005) explored the relations between expectations and attitudes towards new mobile services and how perceptions underlying these expectations and attitudes alter in the immediate period upon trial. Knutsen's investigations suggest that attitudes towards new mobile services are fragile and easily subject to alteration based on first experiences and impressions.

Another line of research from a psychological perspective is to explain mobile communication technology behavior by uncovering people's motivations in using a particular mobile communication technology; for example, Leung and Wei (2000) found mobility, immediacy, and instrumentality the strongest instrumental motives in predicting the use of mobile phones, followed by intrinsic factors such as affection and sociability. Leung and Wei conclude that the same intrinsic or social, instrumental, and psychological reassuring motives of the landline phone are applicable to the mobile phone. Mobility and immediate access are unique dimensions of mobile phone use motivations. Leung and Wei argue that the mobile phone maximizes freedom through mobility, and also benefits from immediate accessibility to the fullest extent. Both factors are instrumental in daily life and work, as well as a facilitating conduit for keeping in touch with family, the aged, and the sick while on the go (p. 316). Leung and Wei state that the mobile phone seems to offer an optimal balance in the long-standing tradeoffs between freedom of movement and immediate access.

Empirical research studies on mobile communication technology use and adoption from a psychological perspective often apply quantitative research methodologies such as large scale surveys and structural equation modeling. Several models based on general social psychological theories of human behavior (e.g., theory of reasoned action, Fishbein & Ajzen, 1975; theory of planned behavior, Ajzen, 1991; social cognitive theory, Bandura, 1986) have been applied to explain and predict mobile communication technology behavior in terms of use and adoption; for example, Kwon and Chidambaran (2000) examined patterns of mobile phone adoption in an urban setting using the technology acceptance model (Davis, Bagozzi, & Warshaw, 1989). Vishwanath and Goldhaber (2003) examined the factors contributing to adoption decisions among late adopters of mobile phones. To examine the relative influence of beliefs, attitudes, and external variables, Vishwanath and Goldhaber synthesized perspectives from the technology acceptance model and diffusion theory into an integrated model of consumer adoption. Nysven, Pedersen, & Thorbjørnsen (2005) put forth an integrated model to explain consumers' intention to use mobile services based on information systems research, uses and gratification research, and domestication research. The model proposes overall influences on usage intention: motivational influences, attitudinal influences, normative pressure, and perceived control. Peters, Rickes, Jöckel, Von Criegern, and Van Deursen (2006) applied the model of media attendance (LaRose & Eastin, 2004) to explain advanced mobile phone services such as email and Internet services. Wang, Lin, and Luarn (2006) respecified and validated an integrated model based on the technology acceptance model and the theory of planned behavior for predicting consumer intention to use mobile communication services from a telecommunication company in order to conduct specific mobile transactions such as mobile shopping and mobile banking. Carlsson, Carlsson, Hyvönen, Puhakainen, and Walden (2006) applied the unified model of acceptance and use of technology (Venkatesh et al., 2003) to explain the acceptance of mobile services such as multimedia messaging service (MMS), search services, and ringtones. Although both the technology acceptance model and the unified model of acceptance and use are adapted from social psychological theories, they originally stem for the field of information systems research. In Chapter 4, three social psychological models to explain and predict mobile communication technology behavior will be presented in more detail.

Other perspectives. Two other empirical disciplines, next to the sociological and psychological research approaches to study mobile communication technology use and adoption, are policy and regulation studies and human-computer interaction from the field of engineering.

Policy and regulation studies on mobile communication technology use and adoption are mostly concerned with the social-economic impact and changing roles of mobile communication technologies in the telecommunications industry, economy, and society. Research studies from this perspective focus on for instance market penetration, regulation policies, and network infrastructure regulations; for example, Blackman, Forge, Bohlin, and Clements (2007) reported findings of a study to forecast user demand for mobile communication services up to 2020. The study used a socio-economic approach including scenarios to explore the future and a methodology for estimating traffic volumes under different socio-economic conditions. Rodini, Ward, and Woroch (2003) estimated the substitutability of fixed and mobile services for telecommunications access. Using a large US household survey conducted over the period 2000-2001, Rodini et al. estimated cross-price elasticities confirming that second fixed line and mobile services are substitutes for one another.

According to Rodini et al., the extent of fixed-mobile substitution has important implications for policy toward fixed network unbundling, fixed-mobile vertical separation, and universal service. Bohlin, Burgelman, and Casal (2007) reflected on the future of mobile communications system in the European Union, addressing a number of mobile technologies, and their respective implications for European growth and competitiveness. Bohlin et al. argue that among the actions to be taken are support for interoperability, through standardization and coordination. Overall there needs to be a greater focus on users who find it difficult to cope with innovation. So far mobile broadband availability is still patchy, expensive and of inadequate quality.

Studies from a human-computer interaction research perspective towards mobile communication technology use and adoption are mainly concerned with usability, ergonomics, and interface design of mobile communication technology; for example, Ziefle (2002) conducted an experiment that was focused on the usability, ease of use and learnability of the menu and navigation keys of three different mobile phones. Overall, the study corroborates the ergonomical vulnerability of the man-machine interface to become of even greater importance with the increasing variety of future functionalities of the mobile phone. Ziefle propose that instead of forcing the user to adapt to the technical solutions, feeling helpless and swamped when handling the technical systems, an interface should be created which accommodates the users' needs.

Yun, Han, Hong, and Kim (2003) investigated the look-and-feel of the mobile phone using a consumer survey. Seventy-eight participants evaluated the design of 50 different mobile telephones on the perceived scale of image and impression characteristics, including: luxuriousness, simplicity, attractiveness, colorfulness, texture, delicacy, harmoniousness, salience, rigidity, and overall satisfaction. The results showed that the image and impression characteristics of the products were closely related to the human-product interface specifications as well as overall shape of the product. Design variables such as texture, use of surface curvature, surface treatment, operating sound, and control response ratio were perceived as important by customers.

2.2 Choice of Research Perspective

This dissertation focuses on the social psychological determinants of mobile communication technology use and adoption. As the several studies above indicate, the social psychological perspective is but one approach to understand mobile communication technology use and adoption. Each of the above-mentioned disciplines contributes in its own way to the mere understanding of people's mobile communication technology use and adoption. However, the social psychological perspective is in contrast to the other disciplines more articulated and advanced in developing and testing empirical models to explain and predict mobile communication technology behavior. Therefore, within this study only social psychological models are evaluated and compared.

Nevertheless it should be acknowledged that mobile communication technology behavior is indeed also influenced by how people treat the technology and how well the technology is designed; people's social economic status and social background; the physical and virtual environment; as well as societal and macro-economical forces. However, because this study focuses on the social psychological determinants of mobile communication technology use and adoption the greater part of these influences on people's mobile communication technology behavior will be left out of consideration in the remainder of this study.

3

Three Theoretical Behavioral Perspectives on Media Use

In this chapter, three theoretical perspectives on the understanding of people's behavior for adopting and using media technology will be presented. First, the expectancy-value perspective on uses and gratifications will be introduced, followed by a social cognitive perspective on media technology behavior. The third perspective is the unified theory of acceptance and use of technology. At the end of the chapter, the convergence between the three perspectives on the central processes and phenomena related to the understanding of media technology behavior will be discussed.

3.1 The Uses and Gratifications Approach and Expectancy-Value Theory

One of the first research approaches in the communication research tradition to focus on media use and adoption is the uses and gratifications approach. According to Bryant and Miron (2004), the year 1959 can be considered as the official birth of the uses and gratifications, when Bernard Berelson claimed that communication research appeared to be dead, and Elihu Katz responded that research should move from what media do to people to what people do with media. Infante, Rancer, and Womack (1997) posit the start of uses and gratifications approach with the first work on uses and gratifications published in 1944 by Lazarsfeld and Stanton on radio research.

At the core of the uses and gratifications approach lies the assumption that audience members actively seek out the mass media to satisfy individual needs. Katz, Gurevitch, and Haas (1973) believed that audience members actively use various media to fulfill certain needs or goals. Katz et al. argued that audience members choose a medium and allow themselves to be swayed, changed, and influenced – or not. Two other assumptions are that audiences also use media to fulfill expectations, and that audience members are aware of and can state their own motives for using mass communication (Infante et al. 1997). According to Infante et al. communication theorists had three objectives in developing uses and gratifications research. First, they hoped to explain how individuals use mass communication to gratify their needs. Secondly, their objective was to discover the underlying motives for individuals' media use. And thirdly, they wanted to identify positive and negative consequences of individual media use, such as parasocial interaction effects (e.g., TV viewing as form of companionship), emotional effects (e.g., to see a movie for entertainment or to escape from everyday life), and behavioral effects (e.g., reading a newspaper to pass time or because it is a habit).

In a more general definition of uses and gratifications, Katz, Blumler, and Gurevitch (1974) posit that uses and gratifications research is "concerned with the social and psychological origins of needs, which generate expectations of the mass media or other sources, which lead to differential patterns of media exposure (or engagement in other activities), resulting in need gratifications and other consequences, perhaps mostly unintended ones" (p. 20).

The most central concept in the uses and gratifications research tradition is probably the concept of gratifications sought (Hendriks Vettehen, 1998, 2002). Despite the importance of the central concept of gratification, a general accepted definition of the concept itself is not easy to find in the rich uses and gratifications literature. Ruggiero (2000) argued that one of the continued flaws in uses and gratifications is that there still exists a lack of clarity among the central concepts and that uses and gratifications researchers attach different meanings to the concepts. Early uses and gratifications researchers were trying to explain media use by an inventory of the consequences of media use people experienced. These experienced gratifications were used to explain media use. Typical for these gratifications is that they are the result of media use. Here lies one of the main critics of the uses and gratifications approach namely that media use is explained by the consequences it has for the user. According to Hendriks Vettehen (1998) it seems that a circular argument is used: use leads to desired gratifications but the desire to receive these gratifications is also the reason for use (p. 17).

A number of media scholars stressed the need to distinguish between the motives for media consumption and the gratifications perceived from this experience (e.g., Greenberg, 1974; Katz et al., 1974; Rosengren, 1974). With the distinction between gratifications sought and gratifications obtained there is no longer a circular argument to explain media use, because media use motives no longer follow the evaluation of media use. As Hendriks Vettehen (1998) illustrated: "The evaluation that watching television on an evening brought some entertaining does not imply that the need for entertainment has been the motive to watch television" (p. 18). By the division of gratifications into two concepts it should be possible in theory to explain the changes in media use by the discrepancy between gratifications sought (motives) and gratifications obtained (evaluation).

The question is whether this theoretical difference between motives and evaluation can also be shown empirically. Hendriks Vettehen (1998, 2002) stated that the analytic difference uses and gratifications researchers make between media use motives and other relevant concepts are not yet empirically distinct. Hendriks Vettehen proposed that an elaborated alternative to the measurement of motivations may be found in the expectancy-value approach, in particular the application of the measurement of b_ie_i as determinant of media exposure (with b_i = belief that some object of exposure possesses attribute i and e_i = evaluation of attribute i).

To provide uses and gratifications with a more solid theoretical basis several authors (e.g., Galloway & Meek, 1981; Rayburn & Palmgreen, 1984) moved away from the origin of needs perspective and incorporated an expectancy-value perspective as used within social psychology (e.g., Fishbein & Ajzen, 1975) into uses and gratifications research.

Although the various theories under the label expectancy-value differ somewhat in their emphases, according to Palmgreen (1984) all view behavior, behavioral intentions, or attitudes (or all three) as a function of (1) expectancy (or belief) – the perceived probability that an object possesses a particular attribute or that a behavior will have a particular consequence; and (2) evaluation – the degree of affect, positive or negative, toward an attribute or behavioral outcome.

Fishbein and Ajzen's (1975) attitude-behavior model, known as the theory of reasoned action, probably constitutes the most influential and well-documented expectancy-value model of attitudes and decision making (Aarts, Verplanken, & Van Knippenberg, 1998). The theory of reasoned action postulates that attitudes (the desirability of the behavior, which is considered to be a function of the sum of the perceived values of the expected consequences of the behavior), together with subjective norms (representing the experienced social pressure), are the antecedents of behavioral intentions, which in turn are supposed to precede behavior. Because the attainment of behavioral goals is not always completely under volitional control, Ajzen (1991) has added a third concept to the prediction of behavior, perceived behavioral control, representing one's perception of how easy or difficult it is to perform the behavior. The inclusion of perceived behavioral control has resulted in the theory of planned behavior.

Infante et al. (1997) stated that there are two major explanations to the expectancy-value mechanism: affective-cognitive consistency (Rosenberg, 1956) and learning theory (Cronkhite, 1969). According to affective-cognitive consistency people have affect and cognitions regarding a topic or object and try to make the two consistent. Affect involves attitude – how favorably people evaluate an object. Cognitions are beliefs about what is related to the object. Affective-cognitive consistency proposes a law of cognitive behavior: if you change a person's belief about a topic, object or proposal, the attitude will "automatically" change in the same direction and to the same degree as the belief changes (Infante et al., 1997, p. 167). According to learning theory, the idea is that people learn to associate consequences with behavior. The response consequences (such as success or failure, or rewards or punishments) influence the likelihood that a person will perform a particular behavior again in a given situation (cf. Stone, 1998).

The expectancy-value perspective is a widely used theoretical approach in studying the adoption, usage and consumption of mass media and also new media technologies. For instance, Babrow and Swanson (1988) extended the application of expectancy-value theory to gratifications research in a study of student exposure to television news. Babrow (1989) used an expectancy-value approach to untangle student perceptions of soap opera viewing. Leung and Wei (1999) examined the use of the pager as newly emerged mass medium for seeking news, focusing on the effects of expectancy-value judgments of the use of the pager in general and on the use of pagers as a news medium in particular on level of exposure to news. More recent Book and Barnett (2006) adopted an expectancy-value approach to examine the potential of PCTV (watching television on your pc) among consumers.

3.2 Social Cognitive Theory

LaRose, Mastro, and Eastin (2001, p. 397) argued that the gratifications sought-gratifications obtained formulation as used by uses and gratifications researchers is "seemingly indistinguishable" from an important mechanism in social cognitive theory; i.e., enactive learning (Bandura, 1986). Enactive learning describes how humans learn from experience. In the social-cognitive view, interactions with the environment influence media exposure by continually reforming expectations about the likely outcomes of future media consumption behavior. Seemingly, this represents the same process that describes the relationship among gratifications sought, media behavior, and gratifications obtained (Palmgreen et al., 1985). Actually, according to LaRose et al., the outcome expectation construct parsimoniously bridges the gulf between gratifications sought and gratifications obtained in uses and gratifications research.

Within social cognitive theory, human behavior is defined as a triadic, dynamic, and reciprocal interaction of personal factors, behavior, and the environment (Bandura, 1986). This triadic causal mechanism is mediated by symbolizing capabilities that transform sensory experiences into cognitive models that guide actions. LaRose and Eastin (2004) posed that within social cognitive theory, behavior is an observable act and the performance of behavior is determined, in large part, by the expected outcomes of behavior, expectations formed by our own direct experience (enactive learning) or mediated by vicarious reinforcement observed through others (observational learning).

Outcome expectations, defined as judgments of the likely consequences of behavior (Bandura, 1997), provide incentives for enacting behavior, whereas expectations of aversive outcomes provide disincentives (Bandura, 1986). Expected outcomes are organized around six basic types of incentives for human behavior (Bandura, 1986, p. 232). These include monetary incentives, social incentives (such as obtaining approval from others), and status incentives. Sensory incentives involve exposure to pleasing or novel sensations. Preferences for enjoyable activities are the basis for activity incentives. There are also internal, self-reactive incentives resulting from comparisons of personal actions with standards for behavior. According to LaRose and Eastin (2004) these incentives are theoretically constructed rather than statistically derived from exploratory factor analysis.

Other concepts from social cognitive theory that are important to understand media technology behavior are self-efficacy and self-regulation. Self-efficacy is the belief in one's capability to organize and execute a particular course of action (Bandura, 1997). Those who perceive themselves to be highly efficacious with reference to a particular task will invest sufficient levels of effort to achieve successful outcomes, whereas those with low levels of self-efficacy will not persist. LaRose and Eastin (2004) posed that self-efficacy is directly related to media usage, and indirectly related to media usage through expected outcomes. Prior experience in turn causally precedes self-efficacy (Eastin and LaRose, 2000), probably through the process of enactive mastery (Bandura, 1986). The social cognitive theory construct of self-regulation (Bandura, 1991) describes how individuals monitor their own behavior, judge it in relation to personal and social standards, and apply self-reactive incentives to moderate their behavior. Within social cognitive theory habit is a failure of the self-monitoring subfunction of self-regulation. A related concept to habit is deficient self-regulation, a state in which conscious self-control is diminished (LaRose & Eastin, 2004).

Although habit and deficient self-regulation have not been clearly empirically distinguished in prior research, LaRose, Lin, and Eastin (2003) proposed a possible theoretical distinction, where habit represents the failure of self-monitoring, and deficient self-regulation represents a failure of the judgmental and self-reactive subfunctions. According to LaRose and Eastin (2004), deficient self-regulation reflects a state of mind distinct from one in which media consumers are inattentive, explaining how both might have independent effects on media attendance. Habit strength and deficient self-regulation should be related by the fact that persons with deficient self-control may also be expected to engage in habitual behavior. Habit strength is expected to influence ongoing behavior. LaRose and Eastin argued that repetition makes us inattentive to the reasoning behind our media behavior; our mind no longer devotes attention resources to evaluating it, freeing itself for more important decisions. LaRose and Eastin posed that habit strength should be causally determined by outcome expectations, which precede habit strength in time. Habit strength should be preceded by self-efficacy, since users are unlikely to be inattentive to behavior they are still mastering.

The comprehensiveness and complexity of social cognitive theory make it somewhat difficult to operationalize and many applications of social cognitive theory focus on one or two constructs, such as for example self-efficacy (e.g., Hofstetter, Zuniga, & Dozier (2001), while ignoring the others (Stone, 1998). Although social cognitive theory is a broad theory of human behavior, it has also been applied to the context of media use. See for instance, Bandura's book chapter "Social cognitive theory of mass communication" in Bryant and Zillman (2001); the study by Hofstetter et al. (2001) to validate the concept of media self-efficacy in using television, newspaper, and interpersonal communication to monitor politics in everyday life; and LaRose, Lai, Lange, Love, and Wu's (2005) study on downloading behavior.

Inspired by Bandura's social cognitive theory, LaRose and Eastin (2004) proposed and tested a new model of media attendance that builds upon the conventional uses and gratifications approach. LaRose and Eastin concluded that the model of media attendance extends the uses and gratifications paradigm within the framework of social cognitive theory by instituting new operational measures of gratifications sought reconstructed as outcome expectations. According to LaRose et al. (2001, p. 399), attempts made by uses and gratifications researchers (e.g., Babrow & Swanson, 1988) to distinguish gratifications from formulations involving outcome expectations were of no avail and failed to produce more robust explanations of media exposure.

3.3 Unified Theory of Acceptance and Use of Technology

In the context of technology acceptance research another perspective on the understanding of people's behavior for adopting and using media technology is proposed; the multi-attribute model of technology use called the technology acceptance model (Davis, 1989). In principle, a multi-attribute model represents a decomposition of a decision problem into smaller and less complex subproblems. The technology acceptance model examines how users come to accept and use a technology (Bagozzi, Davis, & Warshaw, 1992; Davis, Bagozzi, & Warshaw, 1989). According to Venkatesh et al. (2003), information systems research has long studied how and why individuals adopt new information technologies, and the explanation of user acceptance of new technology is often described as one of the most mature research areas in the contemporary information systems literature. Within this broad area of inquiry, there have been several streams of research, and each of these streams makes important and unique contributions to the literature on user acceptance of information technology (Venkatesh et al., p. 427). One stream of research focuses on individual acceptance of technology by using intention or usage as a dependent variable (e.g., Compeau & Higgens, 1995; Davis et al., 1989). Other streams have focused on implementation success at the organizational level (e.g., Leonard-Barton & Deschamps, 1988) and task-technology fit (e.g., Goodhue, 1995), among others.

Technology adoption is one of the most widely researched topics in information systems research. It has been studied at the individual (e.g. Venkatesh et al., 2003), group (e.g., Sambamurthy & Chin, 1994), and organizational (e.g., Fichman & Kemerer, 1997) levels (Venkatesh, 2006). In terms of the reach, the technology acceptance model has been applied in a variety of domains, extending well beyond the initial scope of computer software studied by Davis (1989). According to Venkatesh the technology acceptance model has been applied from marketing contexts (e.g., Dabholkar & Bagozzi, 2002; Gentry & Calantone, 2002; Yang & Peterson, 2004) to green electricity use (Arkesteijn & Oerlemans, 2005) to dairy farming (Flett, Alpass, Humphries, Massey, Morriss, & Long, 2004).

The technology acceptance model replaces many of the attitude measures of the theory of reasoned action (Fishbein & Ajzen, 1975) with two technology acceptance measures: ease of use, and usefulness. The technology acceptance model which has strong behavioral elements, assumes that when someone forms an intention to act, that they will be free to act without limitation. In the real world there will be many constraints, such as limited ability, time constraints, environmental or organizational limits, or unconscious habits that which will limit the freedom to act (Bagozzi et al., 1992).

Venkatesh and Davis (2000) extended the original technology acceptance model to explain perceived usefulness and usage intentions in terms of social influence and cognitive instrumental processes. In an attempt to integrate the main competing user acceptance models, Venkatesh et al. (2003) have formulated the unified theory of acceptance and use of technology. The models Venkatesh et al. reviewed and synthesized into the unified theory of acceptance and use of technology are the theory of reasoned action (Fishbein & Ajzen, 1975), the technology acceptance model (Davis, 1989), the motivational model (Davis, Bagozzi, & Warshaw, 1992), the theory of planned behavior (Ajzen, 1991), a model combining the technology acceptance model and the theory of planned behavior (Taylor & Todd, 1995), the model of PC utilization (Thompson, Higgins, & Howell, 1991), the diffusion of innovations theory (Rogers, 2003), and the social cognitive theory (Bandura, 1986).

The unified theory of acceptance and use of technology comprises four core determinants of intention and usage, and up to four moderates of key relations. Venkatesh, et al. (2003) found four constructs to play a significant role as direct determinants of user acceptance and usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions. The four key moderators in the unified model of acceptance and use of technology are gender, age, experience, and voluntariness of use.

Venkatesh et al. (2003) argued that in terms of explained variance the unified model is a substantial improvement over any of the original eight models and their extensions. Venkatesh et al. posed that the unified theory of acceptance and use of technology provides a useful tool to asses the likelihood of success for new technology introductions and helps to understand the drivers of acceptance in order to proactively design interventions targeted at populations of users that may be less inclined to adopt and use new systems.

3.4 Convergence on Central Processes and Phenomena between the Three Theoretical Perspectives

The presented theoretical perspectives to understand media technology use and adoption each cover broad bodies of literature with rich research traditions behind them, yet they also converge on the central processes and phenomena related to the formation of users' intentions to use media technology, as part of an extended model of media behavior (cf. Stafford, Stafford, & Schkade, 2004).

As already mentioned, Fishbein and Ajzen's (1975) attitude-behavior model, known as the theory of reasoned action, probably constitutes the most influential and well-documented model of attitudes and decision making (see paragraph 3.1). The concepts used in the theory of reasoned action and its successor the theory of planned behavior (Ajzen, 1991) are very similar to the concepts used in another influential theory of human behavior presented in paragraph 3.2, that is social cognitive theory (Bandura, 1986).

According to Stone (1998) social cognitive theory stems from social learning theory, which has a rich historical background dating back to the late 1800's, with its early foundation being laid by behavioral and social psychologists and evolved under the umbrella of behaviorism. While there are several versions of social learning theory to which researchers currently subscribe (Stone, 1998), they all share three basic tenets: (a) response consequences (such as rewards or punishments) influence the likelihood that a person will perform a particular behavior again in a given situation (enactive learning); (b) humans can learn by observing others (observational learning) in addition to learning by participating in an act personally; and (c) individuals are most likely to model behavior observed by others they identify with.

According to the theory of planned behavior (Ajzen, 1991), human behavior is guided by three considerations: beliefs about the likely consequences or other attributes of the behavior (producing a favorable or unfavorable attitude toward the behavior); beliefs about the normative expectations of other people (resulting in perceived social pressure, i.e., subjective norm); and beliefs about the presence of factors that may further or hinder performance of the behavior (that give rise to perceived behavioral control, the perceived ease or difficulty of performing the behavior).

In origin, the expectancy-value theory and social cognitive theory were focused on different psychological phenomena. Where social learning originally was concerned with learning by observation and imitation (e.g., Miller & Dollard, 1941), the perspective gradually moved from social learning and personality development (e.g., Bandura & Walters, 1963) to behavior modification (e.g., Bandura, 1969) and later on to behavioral change (e.g., Bandura, 1977) with the introduction of the concept self-efficacy, which eventually resulted in Bandura's (1986) social cognitive theory.

The expectancy-value theory was originally concerned with the internal processes of human behavior, such as beliefs and attitudes (e.g., Fishbein, 1968; Fishbein & Raven, 1962) which eventually resulted in the theory of reasoned action (Fishbein & Ajzen, 1975), and by adding the concept of behavioral control was extended to the theory of planned behavior (Ajzen, 1991). Conceptually, the concept of perceived behavioral control is by no means new or original to the theory of planned behavior. A similar idea appears in the model of interpersonal behavior (Triandis, 1977), where it takes the form of facilitating conditions. According to Ajzen however perceived behavioral control owes its greatest debt to Bandura's work on self-efficacy (Bandura, 1977, 1986, 1997). Perceived self-efficacy refers to "people's beliefs about their capabilities to exercise control over their own level of functioning and over events that affect their lives" (Bandura, 1991, p. 257).

In retrospect, according to Ajzen (2002) the decision to use the term "perceived behavioral control" to denote this component in the theory of planned behavior may have been misleading, and should be read as "perceived control over performance of a behavior". The term has sometimes been taken to refer to the belief that performance of a behavior affords control over attainment of an outcome. This is according to Ajzen not the intended meaning. Perceived behavioral control simply denotes subjective degree of control over performance of the behavior itself. The distinction here is the same as that between self-efficacy expectations and outcome expectations in social cognitive theory. Ajzen argued that it can be seen that perceived behavioral control and self-efficacy are quite similar: both are concerned with the perceived ability to perform a behavior or sequence of behaviors.

Also, the concept of attitude towards a behavior as used in the theory of reasoned action and theory of planned behavior which is related to the subjective values of the behavior's perceived outcomes – that is, outcome expectations (Ajzen, 2002), is similar to outcome expectations defined as judgments of the likely consequence of behavior (Bandura, 1997) within social cognitive theory.

As described in paragraph 3.3, the unified theory of acceptance and use of technology is constructed out of eight models. However, the theoretical background of these models originates also from either social cognitive theory, the theory of reasoned action, the theory of planned behavior, or a combination of these theories. Even the diffusion of innovations theory is related to social cognitive theory, see for example Bandura's (2006) book chapter 'On Integrating Social Cognitive and Social Diffusion Theories'.

The above-mentioned theoretical connections and similarities between the three theoretical perspectives on media behavior clearly indicate the convergence between the theoretical perspectives with regard to the theoretical concepts used in the three media use models. In the next chapter, a provisional comparison of the three media use models will be presented to illustrate the convergence of the theoretical perspective in more detail. Figure 3.1 shows how the theoretical perspectives and media use models are interrelated.

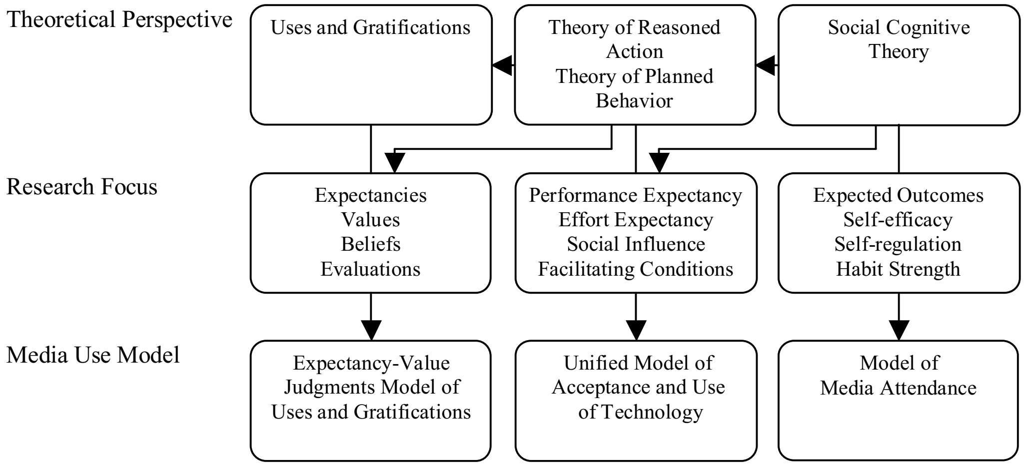

Figure 3.1. Theoretical perspective and research focus of the three media use models.

As a result of the theoretical connections and similarities between the three theoretical perspectives with regard to the central processes and phenomena of interest, it would be interesting to compare the differences in performance of the three media use models to explain and predict media behavior. In the next chapter the media use models and hypotheses that originate from the three theoretical perspectives discussed in this chapter will be described in more detail.

4

Three Social Psychological Media Use Models to Explain and Predict Media Technology Behavior

In the previous chapter, three theoretical behavioral perspectives on media use and adoption were identified. In this chapter the models and hypotheses that originate from these theoretical perspectives will be described in more detail. At the end of this chapter a provisional comparison of the three media use models will be presented.

4.1 The Use of Models in Social Science

Models are commonly constructed in an attempt to approximate or explain some process of scientific interest that cannot be directly observed (Preacher, 2006). In the social sciences, the term 'model' generally refers to either conceptual or causal models depending on the phase in the process of theory building and testing the model is used in. According to the hypothetico-deductive research method – which is based on the assumption that we can best understand complex things by analyzing the various parts or elements that comprise it, the process of theory building and testing consists of four iterative phases: (1) developing questions; (2) forming hypotheses (inductive phase); (3) formulating theory; and (4) testing the hypotheses (deductive phase).

In the inductive phase of model building, conceptual models are specified verbally when first proposed, and constitute a set of assumptions about the structure and function of the phenomenon of interest. When specified in sufficient detail, conceptual models can stimulate a great deal of research, as its predictions are tested and evaluated. Even when a conceptual model is found to be incorrect, the mere existence of the model will have served an important purpose in advancing the understanding and pushing a field forward (Myung, Pitt, & Kim, 2005). This happens by theory building. When a theory is built one can turn to a theoretical deductive description of the model.

In the hypothetico-deductive research tradition, a theoretical deductive description of a model is almost exclusively causally formulated. In other words, causal models posit a temporal relationship between cause and effect. In this regard, causal models take the scientific enterprise a step further to gain new insights into the underlying process and to derive quantitative predictions, which are rarely possible with verbal models (Myung, Pitt, & Kim, 2005). As the three media use models to explain and predict media technology behavior presented in Chapter 3 are all in the deductive phase of theory testing, all three media use models are considered to be causal models.

Causal modeling. The appeal of causal modeling is in the potential it holds for understanding more about the phenomenon of interest. Precise predictions can be tested about how variables should interact or which variables are more dominant than others (Myung, Pitt, & Kim, 2005). In essence, causal modeling allows one to extract more information from the data than for example just ordinal mean differences between variables. Causal modeling enables conceptual verbal theories to be recast into causal models so that a reader can visualize the interconnections of variables (Creswell, 2003, p.122). However, because models can diagram causes and effects, it does not necessarily mean that models actually demonstrate causality (Foster, Barkus, & Yavorsky, 2006). According to Saris and Stronkhorst (1984), an essential element of the notion of causation, is that of 'production' or 'force'. This means that it is hypothesized that a change in one variable (the cause) actually produces a change in another variable (the effect). By contrast, covariation merely refers to the fact that certain scores on one variable are often correlated with certain scores on the other variable (Saris & Stronkhorst, 1984). So if two variables covary with each other, no causal interpretation should be given to this relationship without an explicit verbal formulation of a causal hypothesis.

Myung, Pitt, and Kim (2005) posed that another virtue of causal modeling is that it provides a framework for understanding what can be complex interactions between parts of the model. This is especially true when the model has many parameters. Also causal modeling can help asses how model behavior changes when parameters are combined in different ways. Myung, Pitt, and Kim argued that despite the virtues of causal modeling, it is not risk-free.

Indeed, it can be quite hazardous. It is far too easy for one to unknowingly create an enormous model that will perform well for reasons that have nothing to do with being a good approximation of the phenomenon of interest. The answer to the question how this situation can be identified and avoided or more fundamentally, how a causal model should be evaluated will be discussed in more detail in Chapter 5. In the remainder of this chapter the three causal models that originate from the theoretical perspectives discussed in Chapter 3 will be presented in more detail. At the end of the chapter a provisional comparison of the three media use models will be presented.

4.2 The Expectancy-Value Judgments Model of Uses and Gratifications

The proposition that behavior is guided by the user's perceptions of the probability and value of potential consequences (Fishbein & Ajzen, 1975) has been incorporated in several uses and gratification models (e.g., Galloway & Meek, 1981; Palmgreen & Rayburn, 1985). Babrow and Swanson's (1988) model depicted in Figure 4.1 offers the most completely articulated application of the merger of uses and gratifications approach and the expectancy-value theory.

The expectancy-value judgments model of uses and gratifications suggests that media use behavior is directly determined by behavioral intention and expectancy-value judgments. Behavioral intention is defined as the user's perceived likelihood of performing the behavior (Fishbein & Ajzen, 1985). Expectancy-value judgments are defined as the product of (a) the belief that some object of exposure possesses some attribute, or the belief that exposure to a media object will result in a certain consequence, and (b) the evaluation of that attribute or consequence (Palmgreen & Rayburn, 1985). The following two hypotheses are proposed:

H1: Behavioral intention will have a significant positive influence on media usage
H2: Expectancy-value judgments will have a significant positive influence on media usage

According to the expectancy-value judgments model of uses and gratifications, behavioral intention is directly determined by attitude, subjective norm, and expectancy-value judgments. Attitudes are conceived within the expectancy-value judgments model of uses and gratifications as positive or negative affective responses of the user (Fishbein & Ajzen, 1975). Subjective norm is defined as the user's perceived social expectations, that is, a user' decisions may be influenced by the behavioral expectations of significant social referents (Fishbein & Ajzen, 1975). Accordingly, the following three hypotheses are proposed:

H3: Expectancy-value judgments will have a significant positive influence on behavioral intention
H4: Attitude will have a significant positive influence on behavioral intention
H5: Subjective norm will have a significant positive influence on behavioral intention

According to the expectancy-value judgments model of uses and gratifications, attitude is directly determined by the expectancy-value judgments, which lead to the following hypothesis:

H6: Expectancy-value judgments will have a significant positive influence on attitude

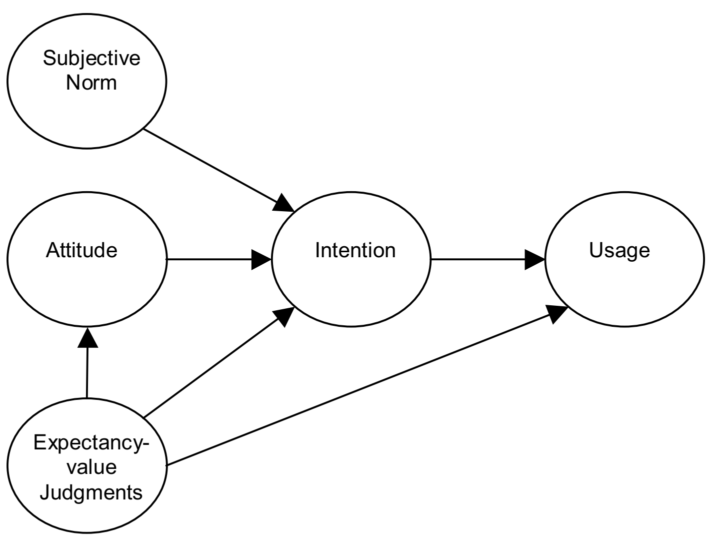

Figure 4.1. The hypothesized expectancy-value judgments model of uses and gratifications.

4.3 The Model of Media Attendance

According to the model of media attendance (LaRose & Eastin, 2004), media usage is directly determined by expected outcomes, self-efficacy, habit strength, and deficient self-regulation. The model is depicted in Figure 4.2. Expected outcomes are defined as judgments of the likely consequences of behavior (Bandura, 1997) and are organized around six basic types of incentives for human behavior: novel sensory, social, status, monetary, enjoyable activity, and self-reactive incentives (Bandura, 1986). Self-efficacy is defined as the belief in one's capability to organize and execute a particular course of action (Bandura, 1997). Within social cognitive theory (Bandura, 1986), habit strength is a failure of the self-monitoring subfunction of self-regulation. LaRose and Eastin argued that through repetition one becomes inattentive to the reasoning behind one's media behavior; the mind no longer devotes attention resources to evaluating it, freeing itself for more important decisions. In the model of media attendance LaRose and Eastin used the construct deficient self-regulation, a state in which conscious self-control is diminished. Where habit represents the failure of self-monitoring, does deficient self-regulation represents a failure of the judgmental and self-reactive subfunctions (LaRose et al., 2003). Habit strength and deficient self-regulation should be related by the fact that persons with deficient self-control may also be expected to engage in habitual behavior (LaRose & Eastin, 2004). The following hypotheses are proposed:

H1: Expected outcomes will have a significant positive influence on media usage
H2: Self-efficacy will have a significant positive influence on media usage
H3: Habit strength will have a significant positive influence on media usage
H4: Deficient self-regulation will have a significant positive influence on media usage
H5: Deficient self-regulation will have a significant positive influence on habit strength

Besides deficient self-regulation, habit strength is also determined by self-efficacy, prior experience, and expected outcomes (LaRose & Eastin, 2004). Accordingly, the following hypotheses are proposed:

H6: Self-efficacy will have a significant positive influence on habit strength

H7: Prior experience will have a significant positive influence on habit strength
H8: Expected outcomes will have a significant positive influence on habit strength

To complete the model of media attendance, self-efficacy is also determined by prior experience; and expected outcomes are determined by self-efficacy. The following two hypotheses are proposed:

H9: Prior experience will have a significant positive influence on self-efficacy
H10: Self-efficacy will have a significant positive influence on expected outcomes

LaRose and Eastin proposed also a relationship between self-reactive outcomes and deficient self-regulation. According to LaRose and Eastin, the use of media to adjust internal states should be the main type of incentive susceptible to triggering the spiral of excessive usage and dysphoria (an emotional state characterized by anxiety, depression, and unease) thought to lead to problematic media usage. Therefore, the following hypothesis is proposed:

H11: Self-reactive outcomes will be positively related to deficient self-regulation

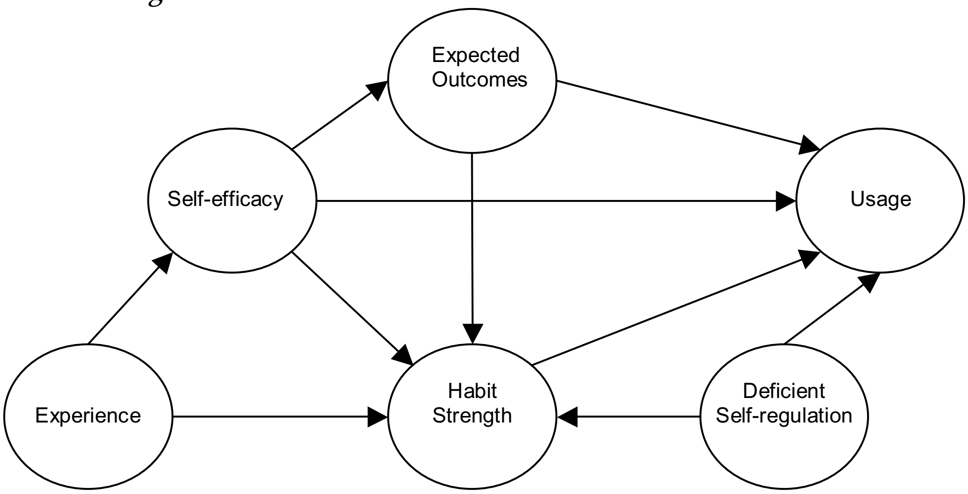

Figure 4.2. The hypothesized model of media attendance.

4.4 The Unified Model of Acceptance and Use of Technology

According to the unified model of acceptance and use of technology (Venkatesh et al., 2003), use behavior is directly determined by behavioral intention and facilitating conditions. The model is depicted in Figure 4.3. Facilitating conditions are defined by Venkatesh et al. as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system. The following hypotheses are proposed:

H1: Behavioral intention will have a significant positive influence on media usage
H2: Facilitating conditions will have a significant positive influence on media usage

According to the unified model of acceptance and use of technology, behavioral intention is determined by performance expectancy, effort expectancy, and social influence. Performance expectancy 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. Effort expectancy is defined as the degree of ease of use associated with the use of the system. Social influence is defined as the degree to which an individual perceives that important others believe he or she should use the system. Accordingly, the following hypotheses are proposed:

H3: Performance expectancy will have a significant positive influence on behavioral intention
H4: Effort expectancy will have a significant positive influence on behavioral intention
H5: Social influence will have a significant positive influence on behavioral intention

Venkatesh et al. (2003) also proposed four key moderators in the unified model of acceptance and use of technology: gender, age, experience, and volutariness of use. The following hypotheses are proposed:

H6a: The influence of performance expectancy on behavioral intention will be moderated by gender and age
H6b: The influence of effort expectancy on behavioral intention will be moderated by gender, age, and experience

H6c: The influence of social influence on behavioral intention will be moderated by gender, age, voluntariness, and experience

H6d: The influence of facilitating conditions on usage will be moderated by age and experience

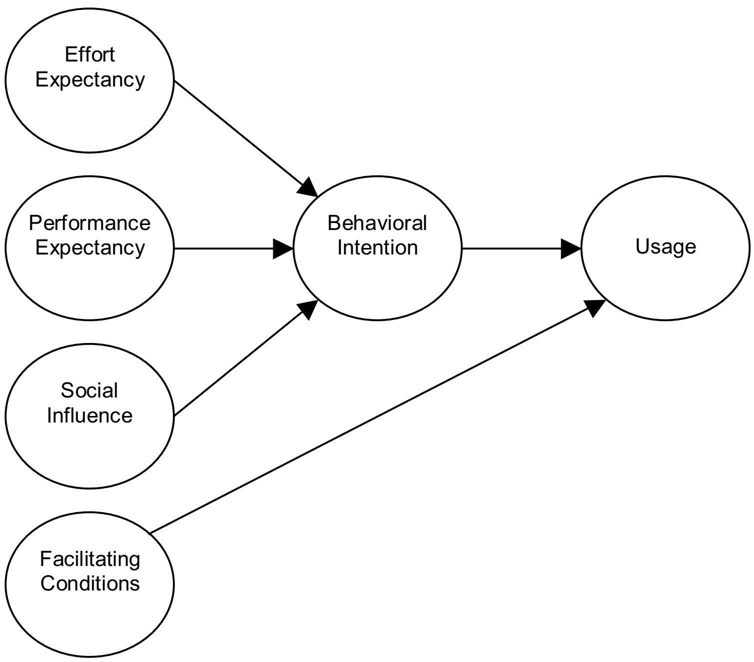

Figure 4.3. The hypothesized unified model of acceptance and use of technology.

The unified theory of acceptance and use of technology does not include self-efficacy and anxiety as direct determinants, although they appeared to be significant direct determinants in social cognitive theory. Previous research (Venkatesh, 2000) has shown self-efficacy and anxiety to be conceptually and empirically distinct from effort expectancy (perceived ease of use). Self-efficacy and anxiety have been modeled as indirect determinants of intention fully mediated by perceived ease of use (Venkatesh, 2000). Consistent with this, Venkatesh et al. (2003) found that self-efficacy and anxiety appear to be significant determinants in social cognitive theory, without controlling for the effect of effort expectancy. Venkatesh et al. therefore expect self-efficacy and anxiety to behave similarly, that is to be distinct from effort expectancy and to have no direct effect on intention above and beyond effort expectancy (p. 455).

Attitude toward using technology defined as an individual's overall affective reaction to using a system is also not included in the unified theory of acceptance and use of technology. Venkatesh et al. posed that attitude is significant only when performance and effort expectancies are not included in the model. Venkatesh et al. consider any observed relationship between attitude and intention to be spurious and resulting from the omission of especially the key predictors performance and effort expectancies.

4.5 Provisional Comparison of the Three Media Use Models

A first provisional examination of the three models to explain and predict media technology behavior shows some striking similarities. This is not surprising because of the convergence of the theoretical concepts used in the three media use models (see Chapter 3). However, also some differences are apparent.

In the first place, all three models have incorporated an expectancy-value mechanism, i.e., expectancy-value judgments in the expectancy-value judgments model of uses and gratifications; expected outcomes in the model of media attendance; and performance expectancy and effort expectancy in the unified model of acceptance and use of technology. Apparently, current expectations of future behavior are important to determine media use behavior.

Also, the influence of significant others is incorporated in all three models. In both the expectancy-value judgments model of uses and gratifications and the unified model of acceptance and use of technology, respectively, subjective norm and social influence are direct determinants of behavioral intention. In the model of media attendance the influence of significant others is represented by social outcomes, which is a direct determinant of media usage and habit strength.

The model of media attendance differs from the other two models with regard to behavioral intention and attitude. The absence of an attitude-intention and an intention-behavior path in the model of media attendance shows that there is a distinct difference between the origins of the three models. Where as the model of media attendance clearly originates from social cognitive theory, the other two models are more an application of the theory of reasoned action.

Because of the strong relationship in the unified model of acceptance and use of technology between performance expectancy and intention, and between effort expectancy and intention, Venkatesh et al. (2003) proposed that attitude does not have a significant influence on behavioral intention and is therefore dropped from the model.

The expectancy-value judgments model of uses and gratifications differs from the other two models with regard to the absence of self-efficacy or facilitating conditions. As already explained in Chapter 3, Ajzen (2002) argued that self-efficacy, facilitating conditions, and perceived behavioral control are quite similar: they all are concerned with the perceived ability to perform a behavior (or sequence of behaviors). Because the attainment of behavioral goals is not always completely under volitional control, Ajzen (1991) has added a third concept to the prediction of behavior to the theory of reasoned action, perceived behavioral control. The inclusion of perceived behavioral control has resulted in the theory of planned behavior. The absence of perceived behavioral control in expectancy-value judgments model of uses and gratifications is understandable since the model originates from the theory of reasoned action.

The expectancy-value judgments model of uses and gratifications differs also from the other two models with regard to the absence of prior experience. Within the model of media attendance prior experience is an indirect determinant of media use behavior mediated via self-efficacy and habit strength. Within the unified model of acceptance and use of technology, prior experience moderates the influence of effort expectancy and social influence on behavioral intention, and facilitating conditions on usage.

Another difference between the unified model of acceptance and use of technology and the other two models is that the focus of the unified model of acceptance and use of technology is mainly on the acceptance and use of technology in an organizational context, where as the two other models are intended to explain and predict media behavior of individuals more in general.

Although, all three models are concerned with the understanding of the same phenomenon of interest, i.e., media technology acceptance and use, all three models propose different determinants to explain and predict media technology behavior. As a result of this observation, it would be interesting to investigate which model best explains and predicts media technology behavior. However, it could also be that each model has its own unique contribution in the explanation and prediction of media technology behavior.

In the next chapter, both empirical and theoretical criteria to systematically evaluate and compare the three causal models will be discussed to ultimately asses which model is paramount in explaining and predicting media technology behavior

5

Model Evaluation and Comparison

In the previous two chapters, three theoretical behavioral perspectives on media use and adoption were identified, and the causal models that originate from these theoretical perspectives were described in more detail. In this chapter, first the criteria to systematically evaluate and compare the three causal models will be discussed. On the basis of a selection of the criteria discussed, the three causal models will be both theoretically and empirically evaluated and compared. The empirical and theoretical evaluation and comparison of the three causal models will be presented in respectively Chapter 7 and Chapter 8.

5.1 Criteria for Model Evaluation and Comparison

The problem of how to choose among competing models is not unique to one particular academic field. It has been studied in depth in several fields, such as psychology, mathematics, ecology, engineering, and computer science. The criteria discussed in this chapter therefore stem from several different disciplines.

Comparing and contrasting models can be fruitful for several reasons (Nigg, Allegrante, & Ory, 2002). Model-comparison research may help, for instance, to avoid Marsh's concept of the 'jingle-jangle' fallacy (Marsh, 1994). The jingle fallacy is assuming that two scales with the same label measure the same construct, and the jangle fallacy is assuming that two scales with different labels measure different constructs. Model comparison can inform if the same constructs are being addressed but labeled differently (jingle), or if the models operationalize the same construct differently (jangle). Also, model comparison can help to learn more about a phenomenon of interest than does any model in isolation. While one model may contribute to the understanding of what motivates an individual to adopt a new media behavior, another model may contribute to the understanding of how an individual maintains that behavior over time. In addition, social-demographic moderators (e.g., ethnicity and age) may differentially influence the effectiveness of psychological models. Finally, comparing and contrasting models may help to understand that the observed variance of some phenomenon of interest cannot be explained at all by existing models, perhaps necessitating the development of entirely new models, and the identification of new variables and novel measurement strategies (Nigg et al., 2002).

Across the practice of science in general, one finds suggestions concerning the goals of scientific theories (Cutting, 2000). A good theory, among other things, should be more accurate, broader in scope, or simpler than its competitors (Kuhn, 1977; Thagard, 1990). Similarly, across social science one finds suggestions that a good model should be descriptively adequate, general, and only as complex as is necessary (Jacobs & Grainger, 1994).

According to Shaw and Constanzo (1970) models differ from theories with regard to the form of explanation. A theory purports to say something about the real world. Shaw and Constanzo defined theory as a set of interrelated hypotheses or propositions concerning a phenomenon or set of phenomena (p. 8). A model, on the other hand, postulates a system that represents the kind of situation that might exist, but is does not necessarily reflect what is "out there" (Shaw & Constanzo, p. 18). According to Shaw and Constanzo, a model describes the phenomena in "as if" terms; therefore, it demonstrates how a particular phenomenon or set of phenomena could occur but not necessarily how it does occur. As (causal) models are derived from theory, the result of model comparison is also instructive for the comparison of their background theories.

Additional criteria for model comparison may therefore be also adopted from related criteria used to compare theories. As with competing theories, models may be also compared to see which model explains better or which model predicts more accurately. If a phenomenon is understood, it can be predicted to the extent that the relevant variables are known and controlled to the extent that one has power over the relevant variables (Shaw & Constanzo, 1970). The goals of describing, explaining, predicting, and controlling which are the primary standards against which theories are tested and evaluated (Infante et al., 1997) may also be applicable to model comparison. Although understanding is the major goal of science, prediction is nevertheless important because it is the process which permits verification of empirical and theoretical generalizations (Shaw & Constanzo, 1970).

5.1.1 Accuracy, Scope, and Simplicity

A first set of criteria for model evaluation and comparison to be discussed is derived from Cutting (2000). Cutting posed that traditionally, models are compared on the basis of their accuracy, their scope, and their simplicity. Similar to assessing the accuracy of a theory, which means that systematic research supports the explanations provided by the theory (Dainton & Zelley, 2004); the accuracy of a model can be assessed by looking at research studies that have used the model and see whether the research supports the model or fails to find support for it. A model's scope is its comprehensiveness or inclusiveness. Scope relies on the principle of generality or the idea that a model must be sufficiently general to extend beyond a single observation (Cushman & Pearce, 1977). Simplicity (also known as parsimony) is often represented by parameter counts. If two models are equally valid, the one with the fewer parameters is said to be the best: the fewer the parameters, the simpler the model (Cutting, 2000).

The problem, however, is that not all criteria seem to have a well-defined basis, and certain criteria will be more important to certain kinds of models. According to Cutting, in both the domains of theory and modeling there is a concern with accuracy, which seems to have a well-defined basis, or at least a well-measured one; with scope, which would seem to have a logical basis, but nonetheless ill-defined; and with simplicity, which often seems to have little more than an aesthetic basis.

Cutting argues that the major problem with the idea of scope is that of demarcation: What lies within the legitimate domain of a theory or model, and what lies outside? Cutting poses that if one could find firm boundaries to a particular domain, one might calculate area or volume or perhaps simply count the numbers of entities within. Any of these could serve as measure of scope and then be used to compare theories or models. However, Cutting argues that boundaries of domains are difficult to determine because they appear to be fuzzy, or even indeterminant. With fuzzy boundaries the notions of demarcation and scope become problematic. According to Cutting, it may be that the only way to compare relative scopes is in situations where the domain of one category appears to lie entirely within the domain of another.

Cutting poses that the concept of simplicity is even more slippery than that of scope. There is an inherent tension between scope and simplicity. On the one hand, one wants a model to fit, and fit as many different data sets as possible (scope). This could be done simply by adding more and more parameters. On the other hand, one wants a model to be a simple as possible (simplicity). This typically means that the number of parameters should be limited. Cutting poses that conceived in this manner, scope will always trade off with simplicity. Also, the notion that a model should explain phenomena with as few variables as possible was not intended to mean economy at the expense of adequacy of theoretical explication (cf. Shaw & Costanzo, 1970). One should be careful with simplicity, as highly parsimonious models may be overly simple and may leave out many important variables that expand the insight into what is happening (cf. Littlejohn & Foss, 2005).

5.1.2 Qualitative and Quantitative Criteria

A second set of criteria for model evaluation and comparison to be discussed is derived from Myung, Pitt, and Kim (2005). Myung, Pitt, and Kim proposed three qualitative criteria (explanatory adequacy, interpretability, and faithfulness) and four quantitative criteria (falsifiability, goodness of fit, complexity, and generalizability) that are thought to be important for model evaluation and comparison. Below, these criteria will be discussed more in detail.

Explanatory adequacy. The first qualitative criterion proposed by Myung, Pitt, and Kim (2005) is explanatory adequacy, which is similar to Cutting's criterion of accuracy. A model satisfies the explanatory adequacy criterion if its assumptions are plausible and consistent with established findings, and importantly, the theoretical account is reasonable for the phenomenon of interest. In other words, the model must be able to do more than redescribe observed data. It should also provide an adequate explanation for the phenomenon of interest supported by substantial theoretical arguments. If a model corresponds with observed data, then the model is an adequate representation of the phenomenon of interest. However, such a correspondence does not guarantee that the theoretical basis of the model and its parameters correspond to the actual processes or cause-effect relationships operating in the real world (cf. Rykiel, 1996). A model should also have the property that every parameter of the model can be given a substantively meaningful interpretation, as the direction of causation and the causal ordering of the constructs cannot be determined by the data (Jöreskog, 1993, p. 298).

Interpretability. The second qualitative criterion proposed by Myung, Pitt, and Kim (2005) is interpretability. A model must be interpretable in the sense that a model makes sense and is understandable. Importantly, the components of the model, especially its parameters, must be linked to theoretical constructs. Model evaluation and comparison may result in accumulating evidence that a model is plausible and consistent with established findings, however this cannot logically prove that the mechanisms contained in the model are theoretically complete and correct (cf. Rykiel, 1996).

Faithfulness. Finally, according to Myung, Pitt, and Kim (2005) a model is said to be faithful to the extent that the model's ability to capture the underlying phenomenon of interest originates from the theoretical principles embodied in the model, rather than from the choices made in its computational instantiation.

Myung, Pitt, and Kim (2005) argued that although, one cannot over-emphasize the importance of the qualitative criteria in model evaluation, they have yet to be quantified. One may doubt whether it is possible or even desirable to quantify qualitative criteria. As such, one may not agree with Myung, Pitt, and Kim that accordingly, one must solely rely on a subjective assessment of a model on each qualitative criterion. Although there are no quantitative measures of the qualitative criteria, the qualitative criteria are substantial, unambiguous and subjected to the scientific discourse. In contrast to the three qualitative criteria for model evaluation and comparison, the four criteria discussed next are quantifiable.

Falsifiability. The first of four quantitative criteria proposed by Myung, Pitt, and Kim (2005) is falsifiability. Falsifiabilty is a necessary condition for testing a model or theory and refers to whether there exist potential observations that a model cannot describe (Popper, 1989). If so, then the model is said to be falsifiable. An unfalsifiable model is one that can describe unerringly all possible data patterns in a given experimental situation. Obviously, there is according to Myung, Pitt, and Kim no point in testing an unfalsifiable model.

Goodness of fit. A model should also provide a good description of the observed data. The goodness of fit criterion refers to the model's ability to fit the particular set of observed data. A fuller discussion of goodness of fit measures, such as Chi^2, the standardized root mean square residual (SRMR), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA) can be found in Chapter 6.

Complexity. The third quantitative criterion Myung, Pitt, and Kim (2005) propose is similar to Cutting's criterion of simplicity. A model should not only describe the data in hand well, it should also do so in the least complex (i.e., simplest) way (Myung, Pitt, & Kim, p. 426). Intuitively, complexity has to do with a model's inherent flexibility that enables it to fit a wide range of data patterns. Myung, Pitt, and Kim poses that there seem to be at least two dimensions of model complexity; the number of parameters and the model's functional form. The latter refers to the way the parameters are combined in the model equation. The more parameters a model has, the more complex it is.

Generalizability. The fourth quantitative criterion for model evaluation proposed by Myung, Pitt, and Kim (2005) is generalizability (similar to Cutting's criterion of scope). This criterion is defined as a model's ability to fit not only the observed data in hand, but also new, as yet unseen data samples from the same probability distribution. In other words, model evaluation should not be focused solely on how well a model fits observed data, but how well it fits future data samples (Myung, Pitt, & Kim, 2005). Since a model's generalizability is not directly observable, it must be estimated using observed data. The measure developed for this purpose trades off a model's fit to the data with its complexity, the aim being to select the model that is complex enough to capture the regularity in the data, but not overly complex to capture the ever-present random variation (Myung, Pitt, & Kim, 2005). Considered in this way, generalizability formalizes the principle of Occam's razor, which states that all things being equal, the simplest solution tends to be the best one. Specific measures of generalizability are the Akaike information criterion (Akaike, 1987), the Bayesian information criterion (Schwarz, 1978), and expected cross-validation (Stone, 1974). In all three methods, the maximized log-likelihood is used as a goodness of fit measure, but they differ in how model complexity is conceptualized and measured. For a fuller discussion of these methods, see Chapter 6.

To summarize, according to Myung, Pitt, and Kim (2005) the four quantitative criteria work together to assist in model evaluation and guide (even constrain) model development and selection. A model must be sufficiently complex, but not too complex, to capture the regularity in the data. Both a good fit to the data and good generalizability will ensure an appropriate degree of complexity, so that the model captures the regularity in the data. In addition, because of its broad focal point, generalizability will constrain the power of a model, thus making it falsifiable.

On the face of it, it seems like goodness of fit should be the main criterion in model evaluation (Myung, Pitt, & Kim, 2005, p. 426). After all, it measures a model's ability to fit observed data. So why not evaluate a model on the basis of its fit? This might be all right if the data reflected only the underlying regularity. According to Myung, Pitt, and Kim, however, data are corrupted by uncontrollable, random variation (noise) due to the inherently stochastic nature of behavioral processes and the unreliable tools used to measure behavior. An implication of noise-contaminated data is that a model's goodness of fit reflects not only its ability to capture the underlying process, but also its ability to fit random noise. This relationship is depicted conceptually by Myung, Pitt, and Kim (p. 427) in the following equation:

Goodness of fit = Fit to regularity (generalizability) + Fit to noise (overfitting)

Myung, Pitt, and Kim argued that the problem is that fitting a data set gives only the overall value of goodness of fit, not the value of the first or second terms on the right-hand side of the equation. Obviously, one is interested in only the first term on the right-hand side of the above equation. This is the quantity that renders the generalizability of the model. The problem is further complicated by the fact that the magnitude of the second term is not fixed but depends upon the complexity of the model under consideration. That is, a complex model with many parameters and a highly nonlinear model equation absorbs random noise easily, thereby improving its fit, independent of the model's ability to capture the underlying process. Consequently, Myung, Pitt, and Kim (p. 427) propose that an overly complex model can fit data better than a simpler model even if the latter generated the data. It is well-established in statistics that goodness of fit can always be improved by increasing model complexity, such as adding extra parameters. Note that a model must possess enough complexity to capture the trends in the data, and thus provide a good fit. After a certain point, additional complexity reduces generalizability because data are overfitted, capturing random variability (Myung, Pitt, & Kim, p. 427). The equation above should clarify that model testing based solely on goodness of fit can result in choosing the wrong (i.e., overly complex) model. Although all four qualitative criteria are interrelated, generalizability may be the most important. It should be the guiding principle in model evaluation and selection (Myung, Pitt, & Kim, p. 426).

5.2 Selected Criteria for Model Evaluation and Comparison

The above presented criteria to systematically evaluate and compare causal models are being used in several disciplines across the practice of science. Similar to the evaluation and comparison of theories (Shaw & Constanzo, 1970), different scientists view some of these criteria as essential and others as desirable but not absolutely essential; for example, Shaw and Constanzo propose that a good theory must be logically consistent. It may not contain contradictory propositions; must also be consistent with accepted facts; and must be able to be disproved or falsified. Shaw and Constanzo believe that these criteria are essential qualities for a good theory, and view them as mandatory. Theories which fail to meet these essential criteria are likely to be rejected.

Compared to criteria for models, Shaw and Constanzo’s mandatory criteria are similar to Myung, Pitt, and Kim’s (2005) criteria of explanatory adequacy and falsifiablity, and Cuttings (2000) criterion of accuracy. Consistent with theory evaluation and comparison, the same criteria are also essential for models in order to be accepted. Each of the three causal models discussed in Chapter 4 comply with these criteria with almost equal weight. Each of the three causal models stems from a broad body of literature within rich research traditions. The three models are falsifiable as several studies have supported each of the three causal models and its assumptions, which might indicate that the assumptions of each model are plausible and consistent with established findings (see Chapter 3).

Since prior research studies (see Chapter 3) have already established that all three causal models are logically consistent, consistent with accepted facts, and testable, with the consequence that all three causal models are generally accepted in the practice of science, one might therefore consider all three models to have met the necessary criteria as a matter of given fact. Consequently, in this dissertation, only the following qualitative and quantitative criteria will be used to theoretically and empirically evaluate and compare the three causal models.

Quantitative criteria. The following statistical measures will be applied as criteria to empirical evaluate and compare the three causal models:

(a) The measures of statistical generalizability: the Akaike information criterion (AIC) and the expected cross-validation index (ECVI);
(b) The explained variance (R^2) of the models to both asses which model explains better and which model predicts more accurately; and
(c) The goodness of fit measures: Chi-square, the standardized root mean square residual (SRMR), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA).

For a detailed discussion of the selected statistical measures, see Chapter 6. The empirical evaluation and comparison of the three causal models will be presented in Chapter 7.

Qualitative criteria. The following theoretical measures will be applied as criteria to theoretically evaluate and compare the three causal models:

(a) Theoretical scope or generality (as opposite to its quantitative counterpart statistical generalizability). Theoretical scope refers to the degree to which a model can be extended to include situations and events not specifically included in the phenomena that the model is supposed to explain. In general (cf. Shaw & Constanzo, 1970), the more comprehensive, the less restrictive, and the more general a model, the more valuable a model is likely to be. However, attempts in this direction may not lead to overgenerality. The danger is that a model will become so all-inclusive that it explains everything and nothing. That is, a model that is so general that it can explain anything that happens cannot be very predictive and contributes little to our understanding of the phenomena of interest;
(b) Theoretical interpretability, to assess whether the parameters in the models are linked to theoretical constructs;

(c) Faithfulness, to asses whether the underlying phenomenon of interest originates from the theoretical principles embodied in the models, rather than from the choices made in its computational instantiation; and
(d) Parsimony or logical simplicity, to asses the economy of the model at the expense of adequacy of theoretical explication.

The theoretical evaluation and comparison of the three causal models will be presented in Chapter 8.

6

Structural Equation Modeling

In this chapter first the structural equation modeling methodology and procedures used in this study will be presented in more detail. Next, an overview of various goodness-of-fit tests will be given. At the end of the chapter, the goodness-of-fit tests and cutoff criteria used in this study to evaluate and compare the three media use models will be summarized.

6.1 Structural Equation Modeling Methodology and Procedures

Communication scholars have enlisted the statistical technique of structural equation modeling for more than a quarter century, analyzing associations among a host of variables that exist at all levels of analysis (Holbert & Stephenson, 2002). Cappella (1975) introduced the field of communication to the strengths, weaknesses, and assumptions of structural equation modeling and outlined how to construct and test a structural equation model. McPhee and Babrow (1987) then completed a critical assessment of the use, disuse, and misuse of this technique in communication from 1976 trough 1985, concluding "what our research community seems to have lacked is a clear format for the general execution and evaluation of path analysis" (p. 364). Holbert and Stephenson's study builds off and expands these works by analyzing the use of structural equation modeling in communication from 1995 through 2000. The general guidelines for the use of structural equation modeling derived from the above-mentioned literature is used as a set of standards to conduct and report causal modeling in this study. In the remainder of this chapter the set of standards, as well as the structural equation modeling methodology and procedures will be presented in more detail.

Structural equation modeling methodology. Structural equation modeling is a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon (Byrne, 2001). Typical, this theory represents “causal” processes that generate observations on multiple variables (Bentler, 1988). Synonyms for structural equation modeling are covariance structure analysis, covariance structure modeling, and analysis of covariance structures (Garson, 2006). According to Byrne, the term structural equation modeling conveys two important aspects of the procedure: (a) that the causal processes under study are represented by a series of structural (i.e., regression) equations, and (b) that these structural relations can be modeled pictorially to enable a clearer conceptualization of the theory under study. The hypothesized model can then be tested statistically in a simultaneous analysis of the entire system of variables to determine the extent to which it is consistent with the data. Bryne poses that if the goodness of fit is adequate, the model argues for the plausibility of postulated relations among variables; if it is inadequate, the tenability of such relations is rejected.

Structural equation modeling approaches. According to Garson (2006) structural equation modeling is usually viewed as a confirmatory rather than exploratory procedure, using one of the three following approaches. The first approach, called the strictly confirmatory approach examines a model using goodness-of-fit tests to determine if the pattern of variances and covariances in the data is consistent with a structural (path) model specified by the researcher. However, as other unexamined models may fit the data as well or better, an accepted model is only a not-disconfirmed model (Garson, 2006). In the second approach, the alternative models approach, one tests two or more causal models to determine which has the best fit. There are many goodness-of-fit measures, reflecting different considerations, and usually three or four are reported by the researcher. The third approach is the model development approach. In practice, much structural equation modeling research combines confirmatory and exploratory purposes: a model is tested using structural equation modeling procedures, found to be deficient, and an alternative model is then tested based on changes suggested by structural equation modeling modification indexes. According to Garson, this is the most common approach found in the literature. The problem with the model development approach is that models confirmed in this manner are post-hoc ones which may not be stable (may not fit new data, having been created based on the uniqueness of an initial dataset). Researchers may attempt to overcome this problem by using a cross-validation strategy under which the model is developed using a calibration data sample and then confirmed using an independent validation sample. Regardless of approach, structural equation modeling cannot itself draw causal arrows in models or resolve causal ambiguities. Theoretical insight and judgment by the researcher is still of utmost importance (Garson, 2006).

Measurement and structural model. According to Holbert and Stephenson (2002) to understand structural equation modeling it is essential to grasp two fundamental concepts: the measurement and structural model. The measurement model establishes relationships between latent (unobserved) variables and multiple observable items. This is the confirmatory factor analysis portion of a model. Latent variables are the underlying constructs not directly tapped by any one set of measures, but they are hypothesized to influence certain observable items in the model. The latent variables are what a researcher ultimately wishes to capture, but which cannot be assessed directly through any one form of observation (Duncan, 1975). The structural model tests a set of hypothesized associations among two or more variables. Holbert and Stephenson argued that many communication scientists have employed structural equation modeling to analyze associations among a set of observable variables (single-item or additive indices), although Jöreskog (1973) and others promote the testing of relationships among latent variables. The associations hypothesized among the variables (latent or observed) constitute the structural component of the model. The measurement and structural models in this study are all latent variable models. The Fornell and Larcker (1981) discriminant validity criterion will be used to test discriminant validity of the latent variables. The Fornell and Larcker criterion is satisfied when a construct is more closely related to its own indicators than to other constructs.

Reporting on causal modeling. Boomsma (2000) encourages authors to provide diagrams of the structural and measurement models, error terms, and correlated parameters. In addition, Hoyle and Panter (1995) suggest that diagrams of the hypothesized and final models be presented, particularly if changes to the hypothesized model were made during estimation. According to Holbert and Stephenson (2002), the statistical theory underlying structural equation modeling is grounded in covariance structure analysis, and the study of covariance matrices is preferred when using this technique (Cudeck, 1989). Authors should provide either the covariance or correlation matrices, and always include standard deviations for others interesting in assessing their work (Boomsma, 2000; Hoyle & Panter, 1995; Rosenthal, 1984).

6.2 The analysis of Categorical Data

According to Holbert and Stephenson (2002), there are several methods of estimation in structural equation modeling one may select from, including maximum likelihood, unweighted least squares, generalized least squares, or asymptotic distribution free estimators. Jöreskog (1973) proposed the use of maximum likelihood to test structural equation models, and this estimator remains the most widely used (Bollen, 1989; Chou & Bentler, 1995). Holbert and Stephenson do not recommend using maximum likelihood with small samples that are multivariate non-normally distributed, as correct models are increasingly likely to be rejected.

However, Byrne (2001) argued that it is important to note that the use of maximum likelihood estimation assumes that the following conditions have been met: (a) the sample is very large, (b) the distribution of the observed variables is multivariate normal, (c) the hypothesized model is valid, and (d) the scale of the observed variables is continuous. Of these four assumptions underlying the use of maximum likelihood estimation in structural equation modeling analyses, the final one concerning scaling has been the subject of considerable debate over the past few years. According to Byrne, essentially, the controversy evolves around the treatment of ordinal scaled variables as if they were of a continuous scale. A typical example is the situation where the data represent item or subscale scores based on Likert-type scale, but they are analyzed using either structural equation modeling or any traditional statistical techniques wherein the assumption is made that the variables are of a continuous scale.

Two primary approaches to the analysis of categorical data were developed by Muthén (1984) and Jöreskog (1990). Both methodologies use limited information estimators based on Browne's (1984) asymptotic distribution-free estimator. Unfortunately, according to Byrne, the positive aspects of these categorical variable methodologies are offset by three major restrictions of importance to practical researchers: (a) the need for very large sample sizes, (b) the limited number of observed variables (less than 25), and (c) the very strong assumption that underlying each categorical observed variable is an unobserved latent variable counterpart that has a continuous scale; furthermore, these latent continuous variables are assumed to be multivariate normally distributed. Because this assumption is extremely strong and may not be appropriate in certain contexts, Chou, Bentler, and Satorra (1991) and Hu, Bentler, and Kano (1992), for example, have argued that it may make more sense to treat the categorical variables as if they were continuous and correct the test statistic, rather than to use a different mode of estimation. Byrne poses that there are some risks involved in treating categorical variables as if they were continuous. First, Pearson correlation coefficients are higher when computed between two continuous variables than when computed between the same two variables reconstructed with an ordered categorical scale. However, the greatest attenuation occurs with variables having less than five categories and those exhibiting a high degree of skewness; the latter condition is made worse by variables that are skewed in opposite directions (i.e., one variable positively skewed, the other negatively skewed). Second, when categorical variables approximate a normal distribution; (a) the number of categories has little effect on the chi-square likelihood ratio test of model fit. Nonetheless, increasing skewness, and particular differential skewness (variables skewed in opposite directions), leads to increasingly inflated chi-square values; (b) factor loadings and factor correlations are only modestly underestimated. However, underestimation becomes more critical when there are fewer than three categories, skewness is greater than 1.0, and differential skewness occurs across variables; (c) error variance estimations, more so than other parameters, appear to be most sensitive to the categorical and skewness issues noted in (b); and (d) standard error estimates for all parameters tend to be low, with the result being more so when the distributions are highly and differentially skewed.

6.3 Model Evaluation and Model Fit

Measures of overall model fit indicate the extent to which a measurement model corresponds to the empirical data. There is no single statistical significance test for evaluating the goodness-of-fit of the model to the data. It is therefore necessary to consider multiple criteria and evaluate model fit on the basis of various measures simultaneously. Holbert and Stephsenson (2002) divide goodness-of-fit indices into two types: absolute fit indices and incremental fit indices. Absolute fit indices evaluate the degree to which the specified model reproduces the sample data. The commonly used absolute fit indices are chi-square statistic, standardized root mean square residual (SRMR), root mean square error of approximation (RSMEA), goodness-of-fit index (GFI) and adjusted goodness-of-fit index (AGFI). Incremental fit indices measure the proportional amount of improvement in fit when a target model is compared with a more restricted, nested baseline model, that is, a null model in which all the observed variables are uncorrelated (Hu & Bentler, 1998). Two commonly used incremental fit indices are non-normed fit index (NNFI), also called the Tucker-Lewis index (TLI) and comparative fit index (CFI). Goodness of fit tests determines if the model being tested should be accepted or rejected.

Garson (2006) argues that these overall fit tests do not establish that particular paths within the model are significant. If the model is accepted, the researcher will then go on to interpret the path coefficients in the model ("significant" path coefficients in poor fit models are not meaningful). Jaccard and Wan (1996) recommend use of at least three fit tests, one from each of the first three categories below, so as to reflect diverse criteria. Kline (1998) recommends at least four tests, such as chi-square, GFI, NFI, or CFI, NNFI, and SRMR. According to Garson, there is wide disagreement on just which fit indexes to report, but one should avoid the “shotgun approach” of reporting all of them, which seems to imply the researcher is on a “fishing expedition”.

Garson (2006) poses that a "good fit" is not the same as strength of relationship: one could have perfect fit when all variables in the model were totally uncorrelated, as long as the researcher does not instruct the structural equation modeling software to constrain the variances. Garson argues that in fact, the lower the correlations stipulated in the model, the easier it is to find "good fit." The stronger the correlations, the more power structural equation modeling has to detect an incorrect model. When correlations are low, the researcher may lack the power to reject the model at hand. Also, all measures overestimate goodness of fit for small samples (less then 200), though RMSEA and CFI are less sensitive to sample size than others (Fan, Thompson, & Wang, 1999). In cases where the variables have low correlation, the structural (path) coefficients will be low also. According to Garson, researchers should report not only goodness-of-fit measures but also should report the structural coefficients so that the strength of paths in the model can be assessed. Readers should not be left with the impression that a model is strong simply because the "fit" is high. When correlations are low, path coefficients may be so low as not to be significant, even when fit indexes show "good fit." Likewise, one can have good fit in a misspecified model. According to Garson, one indicator of this occurring is if there are high modification indexes in spite of good fit. High modification indexes indicate multicollinearity in the model and/or correlated error. A good fit doesn't mean each particular part of the model fits well. Garson argues that many equivalent and alternative models may yield as good a fit - that is, fit indexes rule out bad models but do not prove good models.

Garson poses that fit indexes are relative to progress in the field. Although there are rules of thumb for acceptance of model fit (for example that CFI should be at least .90), Bollen (1989) observes that these cut-offs are arbitrary. A more salient criterion may be simply to compare the fit of one's model to the fit of other, prior models of the same phenomenon; for example, a CFI of .85 may represent progress in a field where the best prior model had a fit of .70. The goodness-of-fit tests presented below are derived from Garson (2006) and summarizes the most relevant goodness-of-fit tests to be used in this study.

Goodness-of-fit tests based on predicted vs. observed covariances. According to Garson (2006), this set of goodness-of-fit measures are based on fitting the model to sample moments, which means to compare the observed covariance matrix to the one estimated on the assumption that the model being tested is true. These measures thus use the conventional discrepancy function. Garson defined the following goodness-of-fit test based on predicted versus observed covariances:

> Model chi-square (χ^2), also called discrepancy or the discrepancy function, is the most common fit test. The chi-square value should not be significant if there is a good model fit, while a significant chi-square indicates lack of satisfactory model fit. That is, chi-square is a "badness of fit" measure in that a finding of significance means the given model's covariance structure is significantly different from the observed covariance matrix. If model chi-square is below .05, the model is rejected. However, the model chi-square test is sensitive to sample size and hence Bentler and Bonnet (1980) suggest using the ratio between chi-square and degrees of freedom as a more appropriate measure of model fit. This ratio should not exceed 5 for models with a good fit (Bentler, 1989).
>
> Goodness-of-fit index (GFI) varies from 0 to 1, but theoretically can yield meaningless negative values. A large sample size pushes GFI up. Though analogies are made to R-square, GFI cannot be interpreted as percent of error explained by the model. Rather it is the percent of observed covariances explained by the covariances implied by the

model. That is, R-square in multiple regression deals with error variance whereas GFI deals with error in reproducing the variance-covariance matrix. As GFI often runs high compared to other fit models, some suggest using .95 as the cutoff. By convention, GFI should by equal to or greater than .90 to accept the model.

Standardized root mean square residual, or standardized RMR (SRMR) is the average difference between the predicted and observed variances and covariances in the model, based on standardized residuals. Standardized residuals are fitted residuals divided by the standard error of the residual (this assumes a large enough sample to assume stability of the standard error). SRMR is 0 when model fit is perfect. The smaller the standardized RMR, the better the model fit. By convention, a value less than .08 indicates a good fit.

Goodness-of-fit tests comparing the given model with an alternative model. According to Garson, this set of goodness of fit measures compares the hypothesized model to the fit of another model. This is well and good if there is a second model. When none is specified, statistical packages usually default to comparing the hypothesized model with the independence model, or even allow this as the only option. The independence model is the null model, which is the model in which variables are assumed to be uncorrelated with the dependent(s). Garson defined the following goodness-of-fit tests comparing the given model with an alternative model:

The comparative fit index (CFI) is also known as the Bentler Comparative Fit Index. CFI compares the existing model fit with a null model which assumes the latent variables in the model are uncorrelated (the "independence model"). That is, it compares the covariance matrix predicted by the model to the observed covariance matrix, and compares the null model (covariance matrix of zero's) with the observed covariance matrix, to gauge the percent of lack of fit which is accounted for by going from the null model to the hypothesized structural model. CFI and RMSEA (see below) are among the measures least affected by sample size (Fan, Thompson, and Wang, 1999). CFI varies from 0 to 1. CFI close to 1 indicates a very good fit. By convention, CFI should be equal to or greater than .90 to accept the model, indicating that 90% of the covariation in the data can be reproduced by the given model.

The normed fit index (NFI) also known as the Bentler-Bonett normed fit index, or simply DELTA1. NFI was developed as an alternative to CFI, but one which did not require making chi-square assumptions. It varies from 0 to 1, with 1 = perfect fit. NFI reflects the proportion by which the hypothesized structural model improves fit compared to the null model (random variables). For instance, NFI = .50 means the researcher's model improves fit by 50% compared to the null model. Put another way, the hypothesized model is 50% of the way from the null (independence baseline) model to the saturated model. By convention, NFI values below .90 indicate a need to respecify the model. NFI may underestimate fit for small samples, according to Ullman (2001).

The non-normed fit index (NNFI), also called the Tucker-Lewis index, TLI, the Bentler-Bonett non-normed fit index, or RHO2. Tthe NNFI is similar to NFI, but penalizes for model complexity. It is one of the fit indexes less affected by sample size. A negative NNFI indicates that the ratio between chi-square and degrees of freedom for the null model is less than the ratio for the given model, which might occur if one's given model has very few degrees of freedom and correlations are low. NNFI close to 1 indicates a good fit. By convention, NNFI values below .90 indicate a need to respecify the model. However, more recently, Hu and Bentler (1999) have suggested NNFI to be equal or higher than .95 as the cutoff for a good model fit.

Goodness-of-fit tests based on predicted vs. observed covariances but penalizing for lack of parsimony. Garson poses that parsimony measures penalize for lack of parsimony, since more complex models will, all other things equal generate better fit than less complex ones. Garson defined the following goodness-of-fit tests based on predicted vs. observed covariances but penalizing for lack of parsimony:

Root mean square error of approximation (RMSEA) is also called RMS or RMSE or discrepancy per degree of freedom. By convention, there is good model fit if RMSEA less than or equal to .05. There is adequate fit if RMSEA is less than or equal to .08. More recently, Hu and Bentler (1999) have suggested RMSEA lower or equal to .06 as the cutoff for a good model fit. A value greater than .10 indicates a poor fit. RMSEA is a popular measure of fit, partly because it does not require comparison

> with a null model and thus does not require the author posit as plausible a model in which there is complete independence of the latent variables as does, for instance, CFI. RMSEA is one of the fit indexes less affected by sample size, though for smallest sample sizes it overestimates goodness of fit (Fan, Thompson, and Wang, 1999). It may be said that RMSEA corrects for model complexity, as shown by the fact that degrees of freedom is in its denominator. However, degrees of freedom (df) is an imperfect measure of model complexity. Since RMSEA computes average lack of fit per degree of freedom, one could have near-zero lack of fit in both a complex and in a simple model and RMSEA would compute to be near zero in both, yet most methodologists would judge the simpler model to be better on parsimony grounds. Therefore model comparisons using RMSEA should be interpreted in the light of the parsimony ratio, which reflects model complexity according to its formula, parsimony ratio = df(model)/df(maximum possible df). Also, RMSEA is normally reported with its confidence intervals.

Goodness of fit measures based on information theory. According to Garson (2006), measures in this set are appropriate when comparing models which have been estimated using maximum likelihood estimation. They do not have cutoffs like .90 or .95. Rather they are used in comparing models, with the lower value representing the better fit. Garson defined the following goodness of fit measures based on information theory:

> The Akaike Information Criterion (AIC) is a goodness-of-fit measure which adjusts model chi-square to penalize for model complexity (that is, for overparameterization). AIC reflects the discrepancy between model-implied and observed covariance matrices. AIC is used to compare models and is not interpreted for a single model. The absolute value of AIC has no intuitive value, except by comparison with another AIC, in which case the lower AIC reflects the better-fitting model.
>
> Expected cross-validation index (ECVI) reflects like AIC the discrepancy between model-implied and observed covariance matrices but penalizes for model complexity (lack of parsimony) more than AIC. Lower ECVI is better fit. When comparing nested models, chi-square difference is normally used. ECVI used for nested models differs from

chi-square difference in that ECVI penalizes for number of free parameters. This difference between ECVI and chi-square difference could affect conclusions if the chi-square difference is a substantial relative to degrees of freedom.

Bayesian Information Criterion (BIC), also known as Akaike's Bayesian Information Criterion (ABIC) and the Schwarz Bayesian Criterion (SBC). BIC penalizes for sample size as well as model complexity. Specifically, BIC penalizes for additional model parameters more severely than does AIC. In general, BIC has a conservative bias tending toward Type II error (thinking there is poor model fit when the relationship is real). Put another way, compared to AIC or BCC, BIC more strongly favors parsimonious models with fewer parameters. BIC is recommended when sample size is large or the number of parameters in the model is small.

6.4 Effect of Number of Variables on Measures of Fit

Kenny and McCoach (2003) argued that there is conflicting evidence as to whether measures of fit tend to improve or decline as more variables are added to the model. The results of their study show that the RSMEA seems to improve as more variables are added to the model. Depending on the type of misspecification, the fit measures for the TLI and the CFI both decline and improve as more variables are added to the model. However, very often these changes are rather small. However, in correctly specified models, the TLI and the CFI tend to demonstrate worse fit as the number of variables in the model increases, whereas RMSEA seems to demonstrate the opposite pattern. Therefore, it appears that the CFI and the TLI do not function well with correctly specified models that include a large number of variables. Given that the TLI and the CFI tend to decline in correctly specified models with large numbers of variables and the RMSEA tends to improve in correctly specified models with large numbers of variables, what should a researcher do? Kenny and McCoach (2003) suggest that researchers simultaneously examine the RMSEA and the CFI or TLI in models with large number of variables. If the TLI and CFI seem slightly lower than hoped, but the RMSEA seems a bit better, then there may be no real cause for concern. However, if a model with large numbers of variables has poor RMSEA and poor TLI or CFI values, which would seem to be a sign of a truly poor fitting model.

6.5 Summary of Cutoff Criteria Used in This Study

In this study, structural equation modeling was undertaken using Amos 6.0 (Arbuckle, 2005). All models are analyzed based on maximum likelihood estimation, with all data being treated as of a continuous scale. Two valuable points support this strategy. First, maximum likelihood estimation is less problematic when the covariance, rather than the correlation matrix, is analyzed; analysis of the latter can yield incorrect standard error estimates (Jöreskog & Sörbom, 1996). Second, when the number of categories is large, the failure to address the ordinality of the data is likely negligible (Atkinson, 1988; Babakus, Ferguson, & Jöreskog, 1987; Muthén & Kaplan, 1985). Indeed, Bentler and Chou (1987, p. 88) argued that, given normally distributed categorical variables, "continuous methods can be used with little worry when a variable has four or more categories."

As suggested by Holbert and Stephenson (2002) the following model fit indices will be used: the Chi-square estimate with degrees of freedom given that it is still the most commonly used means by which to make comparisons across models (Hoyle & Panter, 1995). The ratio between Chi-square and degrees of freedom should not exceed 5 for models with a good fit (Bentler, 1989). Additionally, the standardized root mean squared residual (SRMR) as a second absolute fit statistic (Hu & Bentler, 1999) in combination with the Tucker-Lewis index (TLI) as incremental index and the root mean squared error of approximation (RMSEA) (Browne & Cudeck, 1993) are reported. Hu and Bentler (1999) recommend using a cutoff value close to .95 for TLI in combination with a cutoff value close to .09 for SRMR to evaluate model fit and the RMSEA close to .06 or less. The Akaike information criterion (AIC) is a goodness-of-fit measure which adjusts model chi-square to penalize for model complexity. The absolute value of AIC has no intuitive value, except by comparison with another AIC, in which case the lower AIC reflects the better-fitting model. The expected cross-validation index (ECVI), like AIC reflects the discrepancy between model-implied and observed covariance matrices, but penalizes for model complexity more than AIC. Lower ECVI indicates a better fit. In this study the primary goal is to compare alternative models, therefore the cutoff values of the fit indices will be used more as reference to compare the alternative models than as absolute measure of model fit.

7

Empirical Comparison of Three Models to Explain and Predict Mobile Communication Technology Behavior

In the previous two chapters, the criteria to systematically evaluate and compare the three causal models were discussed. In this chapter the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology are evaluated and compared in the context of mobile phone use as well as in the context of mobile video phone adoption on the basis of the empirical criteria proposed in chapter 5. The findings of the theoretical evaluation and comparison of the three models will be discussed more in detail in chapter 8.

7.1 Sample and Procedures

To empirically evaluate and compare the three models discussed in Chapter 4 within the same user context, the original items of all three models were rephrased in the context of mobile communication technology use and adoption. The Netherlands (91%) together with Finland (93%) and Sweden (93%) are according to a survey commissioned by the European Commission (2006) the countries with the highest penetration rate of mobile phones in Europe. The average rate of mobile phone penetration in Europe is 80 percent. The high penetration rate of mobile phones in the Netherlands is very appropriate to compare the different models to explain mobile communication technology use. Recent developments in the mobile communication industry make it possible to add all kinds of advanced attributes to mobile communication technology devices, like for example video telephony. With mobile video telephony people can not only talk to each other, but they also can see each other. This new added feature of mobile video communication technology is now available on mobile phones in the Netherlands and mobile phone operators are starting to promote this new service which requires wireless broadband access. The intention of mobile phone users to start using this new technology of mobile video telephony to communicate with other people is a perfect opportunity to compare the different models with regard to predicting mobile communication technology adoption.

Table 7.1
Summary of Demographics,
Mobile Phone Experience, Mobile Phone Use, and SMS Use

	Group I (n = 310)	Group II (n = 334)	Group III (n = 320)
Gender[a]: Male	44%	43%	44%
Female	56%	57%	56%
Age[b]: < 20	4%	4%	2%
20 – 40	38%	45%	38%
40 – 60	47%	40%	49%
60 >	11%	11%	11%
Education[c]: High school or less	33%	31%	30%
Vocational education	26%	27%	29%
Bachelor degree	31%	31%	31%
Master degree	10%	11%	10%
Mobile phone experience (years)[d]	6.60 (2.89)	6.90 (2.84)	6.80 (3.15)
Mobile phone use (times a day)[e]	2.88 (3.97)	3.29 (5.64)	3.42 (4.76)
SMS use (times a day)[f]	1.64 (2.33)	1.72 (2.68)	1.71 (3.00)

Note. [a]$\chi^2(2, N = 964) = .06, p > .05$. [b]$\chi^2(6, N = 964) = 8.92, p > .05$. [c]$\chi^2(6, N = 964) = 2.32, p > .05$. [d]$F(2, 961) = .89, p > .05$. [e]$F(2, 961) = 1.06, p > .05$, [f]$F(2, 961) = .09, p > .05$.

Stratified random sampling method. Subscribers of a national panel (N = 1299) which represents the Dutch population administrated by a for-profit research and consultancy company were invited via email to voluntarily participate in the online survey. To forestall common method bias, each measurement instrument of the three models should not be subjected to one and the same sample of respondents; therefore the 964 mobile phone users who responded to the invitation (74.21% response rate) were divided into three equal subsamples using a stratified random sampling method considering demographics, mobile phone use, and mobile phone experience as strata. Pearson's chi-square test and one-way ANOVA for independent samples were used to test for differences between the three subsamples. No significant differences between the three groups of respondents were found with regard to demographics, mobile phone experience, mobile phone use, and SMS use (see Table 7.1). Since the three groups of respondents do not differ with regard to the strata; differences found between the three models therefore may not be attributed to differences between the three groups of respondents.

Research Design. To empirical evaluate and compare the three models in the context of mobile phone use as well as in the context of mobile video phone adoption the following research design depicted in Figure 7.1 was utilized.

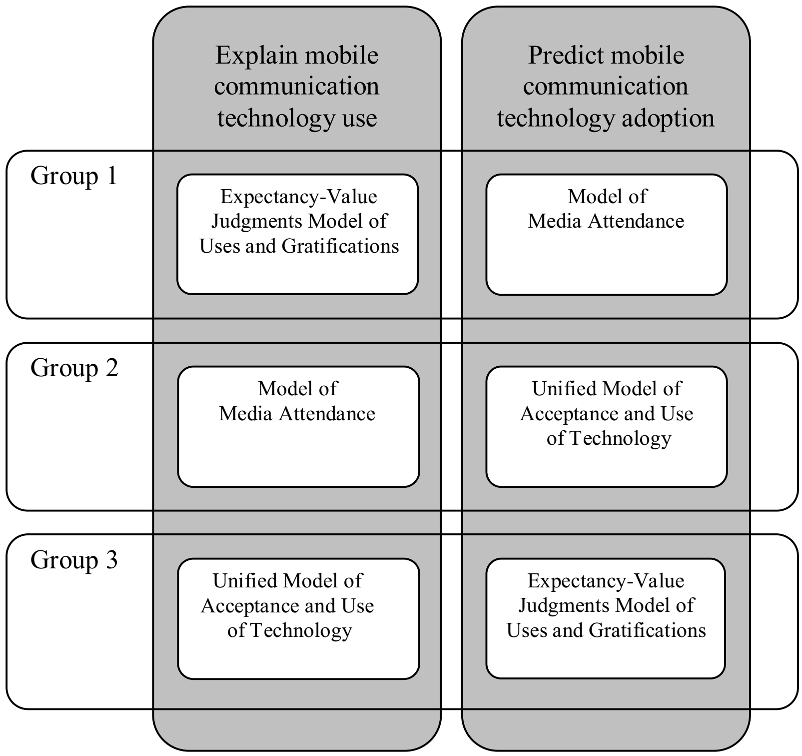

Figure 7.1. Research design of the study

Mobile communication technology use. To empirically compare the three models in terms of the explanation of mobile communication technology use, respondents of group one (n = 310) were surveyed on existing mobile phone use to empirically test the expectancy-value judgments model of uses and gratifications (Babrow & Swanson, 1988); respondents of group two (n = 334) were surveyed on existing mobile phone use to empirically test the model of media attendance (LaRose & Eastin, 2004); and respondents of group three (n =

320) were surveyed on existing mobile phone use to empirically test the unified model of acceptance and use of technology (Venkatesh, et al., 2003).

Mobile communication technology adoption. To empirically compare the three models in terms of predicting mobile communication technology adoption, respondents of group one were also surveyed on the intention to adopt mobile video phone to empirically test the model of media attendance; respondents of group two were also surveyed on the intention to adopt mobile video phone to empirically test the unified model of acceptance and use of technology; and respondents of group three were also surveyed on the intention to adopt mobile video phone to empirically test the expectancy-value judgments model of uses and gratifications.

Mobile video phone device. At the beginning of the mobile video phone survey, a detailed picture of a mobile video phone device with a description of its functionalities was used to introduce the technology (see Figure 7.2).

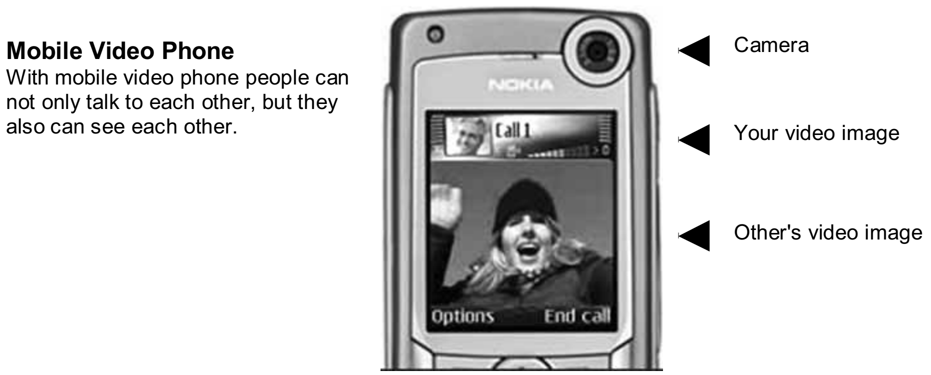

Figure 7.2. Detailed picture of a mobile video phone device

7.2 Expectancy-Value Judgments Model of Uses and Gratifications

To empirically test the expectancy-value judgments model of uses and gratifications, both the measurement and structural model of the expectancy-value judgments model of uses and gratifications were developed to successively explain mobile phone use and to predict mobile video phone adoption. The original items by Babrow and Swanson (1988) to explain student exposure to television news were rephrased in the context of mobile communication technology use and adoption. Substituted items were collected from prior research on uses and gratifications of the mobile phone (i.e., Leung & Wei, 2000).

Pre-test. Under-graduate students (N= 62) from both the departments of Communication Studies and Psychology at the University of Twente in the Netherlands participated in a pre-test of the expectancy-value judgments model of uses and gratifications for research experience points. The items were pre-tested on legibility and internal consistency. Furthermore, items with highly correlated error variances and items that loaded poorly onto its unique factor were removed. This procedure resulted in a reduction of the number of observed indicators of the latent constructs. The internal consistency of both the measures to explain mobile phone use and the measures to predict mobile video adoption were above aspiration level (Cronbachs's α > .70), except for the attitude measures. Respondents had a wrong connotation to the attitude scale with the endpoints 'extremely harmful/beneficial'. The use of a mobile phone or mobile video phone can be beneficial in terms of instrumental use, but also not very beneficial in terms of costs. The endpoints of the attitude scale were replaced with the endpoints 'worthless/valuable'.

7.2.1 Measures

Mobile phone behavior. Respondents were asked to estimate the number of times they used a mobile phone to make a phone call on an average weekday. Similarly, respondents were asked to estimate the number of times they used a mobile phone to send a Short Message Service (SMS) message on an average weekday.

Behavioral intention, subjective norm, and attitude. Three intention measures asked the respondents to rate their intention to use a mobile phone in the next week on a seven-point bipolar scale ranging from 1 (*extremely unlikely*) to 7 (*extremely likely*). The three intention measures were: 'I intend to use a mobile phone in the next week', 'I predict I would use a mobile phone in the next week', and 'I plan to use a mobile phone in the next week'. To assess subjective norm, respondents rated whether people important to them thought they should use a mobile phone. A single seven-point scale ranging from 1 (*should*) to 7 (*should not*) provided the score. As measure of attitude, respondents rated the use of a mobile phone on three seven-point bipolar scales ranging from 1 to

7. The scale endpoints were defined as 'extremely unpleasant/pleasant', 'extremely unimportant/ important', and 'extremely worthless /valuable'.

Mobile phone expectancy-value judgments. Previous research on uses and gratifications of the mobile phone (i.e., Leung & Wei, 2000) identified four gratification factors: mobility, affection/sociability, instrumentality, and immediate access. Twelve core items were bases for measures of the expectancy-value judgments (see Table 7.2). To measure the expectancy-value judgments, respondents evaluated each of the 12 items on seven-point bipolar scales ranging from -3 (*extremely bad feature*) to 3 (*extremely good feature*). The probability that the use of a mobile phone provides each of the 12 gratifications was recorded on seven-point scales ranging from 0 (*very likely does not have this feature*) to 6 (*very likely to have this feature*). The expectancy-value judgments scores were composed from the product of the two seven-point scales.

Table 7.2

Core Expectancy-Value Judgments Items to Explain Mobile Phone Use

Mobility
Because I can use it whenever it suits me
Because it allows me to instantly call someone wherever I am
Because I can use it everywhere
Because I can take it with me anywhere
Affection/Sociability
To strengthen my relationship with family and friends
To maintain contact with family and friends
To keep my family and friends informed
Permanent Access
To be accessible to others whenever and wherever I am
To be instantly accessible wherever I am
Instrumentality
To make appointments
To organize matters
To arrange affairs

Behavioral intention to use mobile video phone, subjective norm, and attitude. Three intention measures asked the respondents to rate their intention to use mobile video phone in the next three months on a seven-point bipolar scale ranging from 1 (*extremely unlikely*) to 7 (*extremely likely*). The three intention measures were: 'I intend to use mobile video phone in the next three months', 'I predict I would use mobile video phone in the next three months', and 'I plan to use mobile video phone in the next three months'. To assess subjective norm, respondents rated whether they thought people important to them were going to use mobile video phone. A single seven-point scale ranging from 1 (*they will not*) to 7 (*they will*) provided the score. As measure of attitude, respondents rated the expected use of mobile video phone on three seven-point bipolar scales, ranging for 1 to 7. The scale endpoints were defined as 'extremely unpleasant/pleasant', 'extremely unimportant/important', and 'extremely worthless/valuable'.

Table 7.3

Core Expectancy-Value Judgments Items to Predict Mobile Video Phone Use

Novelty
To try out something new
Because it's something new
To communicate in a new way
Because it adds something new
Fashion/Status
To have it as a status symbol
To look stylish
To distinguish myself from others
Affection/Sociability
To strengthen my relationship with family and friends
To maintain contact with family and friends
To keep my family and friends informed
Relaxation
To have fun
To enjoy
To have a pleasant conversation

Mobile video phone expectancy-value judgments. Inspired by previous research on uses and gratifications of the mobile phone (i.e., Leung & Wei, 2000) four gratification factors were developed: novelty, fashion/status, relaxation, and affection/sociability. Twelve core items were bases for measures of expectancy-value judgments (see Table 7.3). To measure the expectancy-value judgments, respondents evaluated each of the 13 items on seven-point bipolar scales ranging from -3 (*extremely bad feature*) to 3 (*extremely good feature*). The probability that the use of mobile video phone provides each of the 13 gratifications was recorded on seven-point scales ranging from 0 (*very likely does not have this feature*) to 6 (*very likely to have this feature*). The expectancy-value judgments scores were formed from the product of the two seven-point scales.

7.2.2 Explaining Mobile Phone Use

Prior to the analyses, data were checked for normality. Because of skewness to the upper end of the distribution of the measures mobile phone usage and SMS usage, a square-root transformation was performed to correct skew (cf. Garson, 2006).

Using a first-order confirmatory factor analysis, the measurement model estimated the extent to which the observed items loaded onto their respective latent variables. Because subjective norm was measured with a single observed item, it was not included in the measurement model. All latent constructs but no observed error variances were allowed to co-vary with one another.

Measurement model. The measurement model of the expectancy-value judgments model generated a good fit, $\chi^2(149) = 280.58$, $\chi^2/df = 1.88$, SRMR = .048, TLI = .961, RMSEA = .053 (90% confidence interval [CI]: .044, .063). The internal consistency of the measures to explain mobile phone use was above aspiration level ($\alpha > .70$). The correlation matrix of the observed variables, subjective norm, mobile phone usage, and SMS usage is shown in Table 7.4.

Structural model. The results obtained from testing the validity of a causal structure of the hypothesized expectancy-value judgments model of uses and gratifications showed an adequate fit, $\chi^2(180) = 416.17$, $\chi^2/df = 2.31$, SRMR = .076, TLI = .937, RMSEA = .065 (CI: .057, .073), AIC = 518.17, ECVI = 1.68 (CI: 1.50, 1.88). Table 7.5 summarizes the original (uncorrected) mean and standard deviation, Cronbach's α, the factor loading (β), and the squared multiple correlation (R^2) of the observed indicators to explain mobile phone use.

Path model. The path model with standardized path coefficients is featured in Figure 7.3. The standardized path coefficients in Figure 7.3 show significant direct effects of behavioral intention and expectancy-value judgments on mobile phone usage. Figure 7.3 also show significant direct effects of attitude and expectancy-value judgments on behavioral intention; and a significant direct effect of expectancy-value judgments on attitude. The direct effect of subjective norm on behavioral intention is not significant. Mobility was the strongest contributor of expectancy-value judgments, followed by instrumentality, permanent access, and affection/sociability. Although the direct effect of behavioral intention on mobile phone usage is stronger than the direct effect of expectancy-value judgments, the total effect of expectancy-value judgments on mobile phone usage mediated via attitude and behavioral intention ($\beta = .64$) equals the direct effect of behavioral intention on mobile phone usage. Furthermore, there was a significant total effects of expectancy-value judgments ($\beta = .55$) on behavioral intention mediated via attitude; and a significant indirect effect of attitude ($\beta = .14$) on mobile phone usage mediated via behavioral intention. Squared multiple correlations showed that attitude was accounted for 57%, behavioral intention was accounted for 31%, and mobile phone usage was accounted for 69% (see Table 7.5).

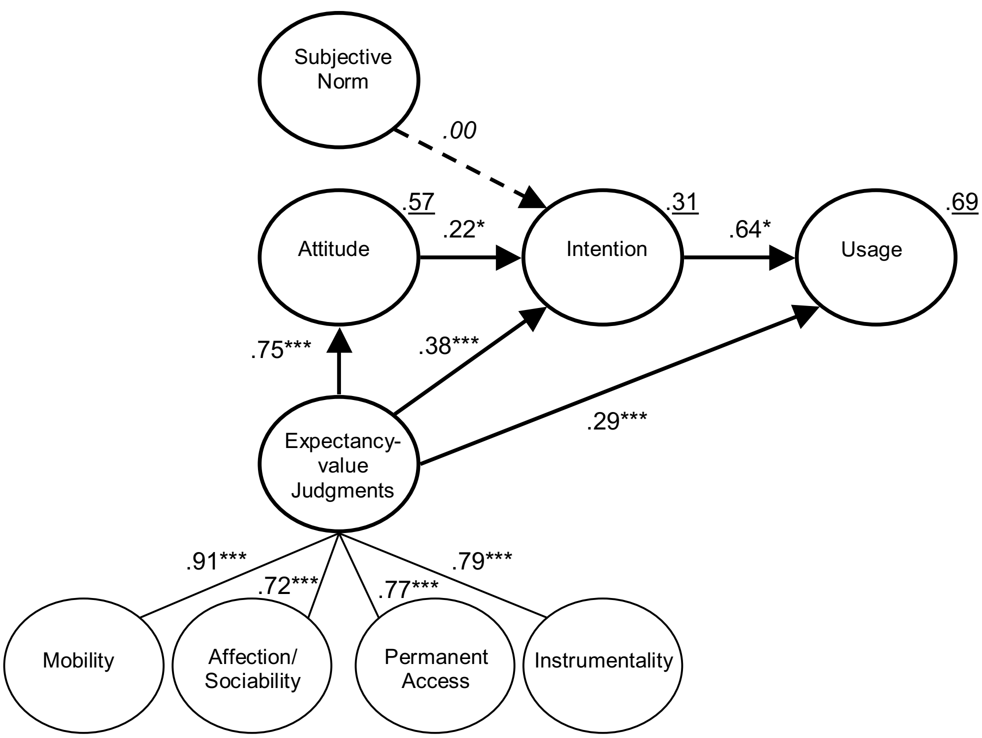

Figure 7.3. Standardized path coefficients of the expectancy-value judgments model of uses and gratifications to explain mobile phone usage. The observed indicators of the latent construct are not shown (see Table 7.5).
Note. $^{*}p < .05$, $^{***}p < .001$. Dotted lines are non-significant paths (non-significant factor loadings in Italic). Squared multiple correlations are underlined.

Table 7.4

Correlation Matrix of the Observed Expectancy-Value Judgments Variables, Subjective Norm, Mobile Phone Usage, and SMS Usage

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	MOB1	-	.58	.66	.63	.40	.34	.37	.50	.54	.46	.48	.40	.49	.44	.39	.41	.45	.43	*.11*	.19	.17
2	MOB2		-	.61	.63	.55	.42	.45	.54	.55	.54	.54	.48	.44	.37	.35	.45	.46	.48	.13	.19	.24
3	MOB3			-	.66	.38	.38	.39	.55	.57	.46	.49	.43	.48	.40	.41	.42	.39	.42	.18	.15	.18
4	MOB4				-	.43	.38	.44	.52	.56	.49	.54	.44	.41	.39	.34	.38	.38	.38	16	.15	.17
5	AS1					-	.57	.67	.44	.41	.59	.51	.47	.43	.39	.38	.32	.32	.32	.23	.18	.30
6	AS2						-	.78	.41	.42	.52	.51	.56	.34	.33	.36	.20	.22	.22	.18	*.06*	.27
7	AS3							-	.35	.40	.59	.62	.58	.36	.35	.37	.20	.22	.23	.23	*.10*	.32
8	PA1								-	.80	.43	.41	.38	.43	.41	.34	.32	.35	.35	.23	.13	.13
9	PA2									-	.53	.48	.46	.42	.35	.32	.35	.37	.36	.23	.15	*.14*
10	INS1										-	.77	.72	.44	.36	.39	.33	.36	.35	.15	.33	.30
11	INS2											-	.84	.42	.34	.40	.32	.34	.34	.15	.33	.26
12	INS3												-	.39	.31	.36	.25	.27	.26	.17	.31	.25
13	ATT1													-	.56	.58	.39	.39	.43	*.11*	.22	.19
14	ATT2														-	.44	.30	.32	.31	.24	.12	.14
15	ATT3															-	.25	.29	.30	*.07*	*.06*	.32
16	INT1																-	.86	.88	.13	.31	.28
17	INT2																	-	.89	*.09*	.31	.29
18	INT3																		-	.14	.33	.30
19	SN																			-	*.09*	*.07*
20	PHONE																				-	.22
21	SMS																					-

Note. Significant at $p < .05$, non-significant correlations are in Italic. MOB = mobility, AS = affection/sociability, PA = permanent access, INS = instrumentality, ATT = attitude, INT = behavioral intention, SN = subjective norm, PHONE = mobile phone use, SMS = SMS use.

Table 7.5

Descriptive Statistics, Factor Loadings, Squared Multiple Correlations, and Cronbach's Alpha of the Observed Indicators to Explain Mobile Phone Use

	M	*SD*	β	R^{2b}
Usage				.69
Mobile phone (*typical weekday)*	2.88	3.97	.60	.35
SMS *(typical weekday)*	1.64	2.33	.51	.26
Behavioral intention (α = .95)				.31
I intend to use a mobile phone in the next week	5.97	1.80	.92	.85
I predict I would use a mobile phone in the next week	5.89	1.88	.93	.86
I plan to use a mobile phone in the next week	5.88	1.87	.95	.91
Attitude (α = .77)				.57
Extremely unpleasant/pleasant	4.70	1.40	.83	.69
Extremely unimportant/important	4.62	1.40	.67	.45
Extremely worthless/valuable	4.16	1.47	.69	.47
Mobility (α = .87)[a]				.82
I can use it whenever it suits me	11.80	5.37	.78	.61
It allows me to instantly call someone wherever I am	9.08	7.03	.81	.65
I can use it everywhere	10.52	6.38	.78	.61
I can take it with me anywhere	8.66	7.34	.81	.66
Affection/Sociability (α = .91)[a]				.52
To strengthen my relationship with family and friends	5.30	6.41	.84	.70
To maintain contact with family and friends	1.82	5.09	.92	.85
To keep my family and friends informed	2.37	5.70	.73	.54
Permanent Access (α = .89)[a]				.59
To be accessible to others whenever and wherever I am	7.45	7.97	.93	.86
To be instantly accessible wherever I am	6.30	7.77	.87	.75
Instrumentality (α = .91)[a]				.62
To make appointments	4.38	6.68	.83	.69
To organize matters	4.72	6.45	.94	.89
To arrange affairs	3.46	6.09	.88	.78
Subjective norm	4.58	2.22		

Note. [a]The means and standard deviations of expectancy-value judgments are for 37 point scales (-18 to +18) formed from the product of two seven point scales: evaluations ranging from -3 = "extremely bad feature" to +3 = "extremely good feature", and beliefs ranging from 0 = "definitely does not have feature" to 6 = "definitely does have feature".

[b]The R^2 of a latent dependent predictor is the percent of the variance in the latent dependent variable accounted for by the latent independent variable. The R^2 of an observed indicator is the estimated percent variance explained in that variable. In other words, the error variance of a variable is approximately 1 minus the percent of the variance of the variable itself.

7.2.3 Predicting Mobile Video Phone Adoption

Prior to the analyses, data were checked for normality. Because of skewness to the lower end of the distribution of the measure mobile video phone intention, an inverse (reciprocal) transformation was performed to correct skew (Garson, 2006).

Using a first-order confirmatory factor analysis, the measurement model estimated the extent to which the observed items loaded onto their respective latent variables. Because subjective norm was measured with a single observed item, it was not included in the measurement model. All latent constructs but no observed error variances were allowed to co-vary with one another.

Measurement model. The measurement model of the expectancy-value judgments model of uses and gratifications generated an adequate fit, $\chi^2(137) = 337.27$, $\chi^2/df = 2.46$, SRMR = .048, TLI = .952, RMSEA = .068 (CI: .059, .077). The internal consistency of the measures to explain mobile phone use was above aspiration level ($\alpha > .70$). The correlation matrix of the observed variables and mobile video intention is shown in Table 7.6. The correlation matrix shows that the indicators of novelty are also closely related to the indicators of affection/sociability and the indicators of relaxation.

Structural model. The results obtained from testing the validity of a causal structure of the hypothesized expectancy-value judgments model of uses and gratifications showed an adequate fit, $\chi^2(163) = 419.72$, $\chi^2/df = 2.58$, SRMR = .086, TLI = .943, RMSEA = .070 (CI: .062, .079), AIC = 513.72, ECVI = 1.61 (CI: 1.43, 1.81). Table 7.7 summarizes the original (uncorrected) mean and standard deviation, Cronbach's α, the factor loading (β), and the squared multiple correlation (R^2) of the observed indicators to predict mobile video phone use.

Path model. The path model with standardized path coefficients is featured in Figure 7.4. The standardized path coefficients in Figure 7.4 show significant direct effects of expectancy-value judgments and subjective norm on mobile video phone intention. Also, Figure 7.4 shows a significant direct effect of expectancy-value judgments on attitude. The direct effect of attitude on mobile video phone intention is not significant. Relaxation and novelty were the strongest contributors of expectancy-value judgments, followed by affection/sociability and fashion/status. Squared multiple correlations showed that attitude was accounted for 30% and mobile video phone intention was accounted for 22% (see Table 7.7).

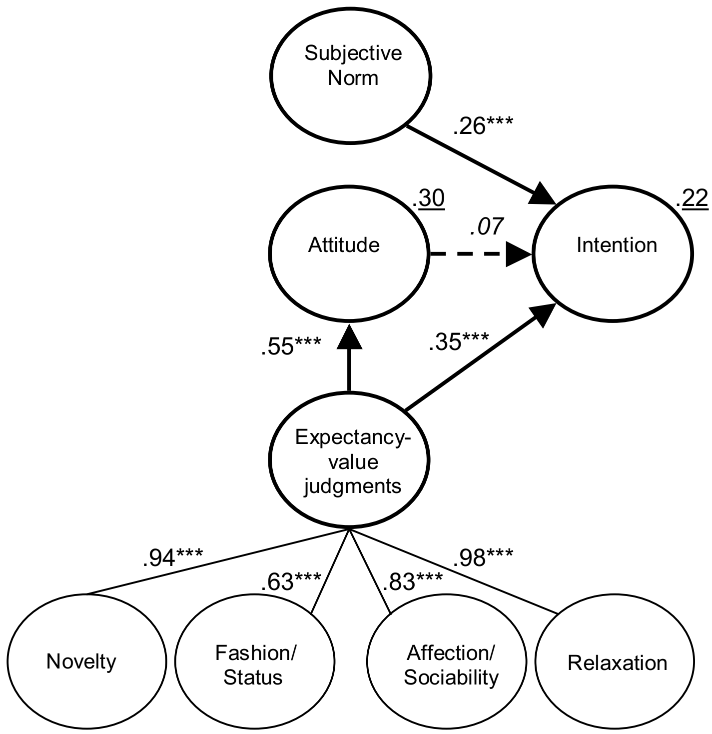

Figure 7.4. Standardized path coefficients of the expectancy-value judgments model of uses and gratifications to predict mobile video phone adoption. The observed indicators of the latent construct are not shown (see Table 3).
Note. ***p < .001. Dotted lines are non-significant paths (non-significant factor loadings in Italic). Squared multiple correlations are underlined.

Table 7.6

Correlation Matrix of the Observed Expectancy-Value Judgments Variables, Subjective Norm, and Mobile Video Phone Intention

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	NOV1	-	.68	.49	.62	.31	.39	.41	.44	.47	.49	.55	.62	.59	.31	.21	.31	.29	.45	.44	.44
2	NOV2		-	.53	.67	.31	.42	.41	.53	.61	.64	.64	.70	.66	.32	.26	.37	.35	.49	.49	.49
3	NOV3			-	.45	.23	.36	.33	.49	.59	.53	.71	.62	.55	.28	.18	.31	.21	.52	.49	.51
4	NOV4				-	.26	.41	.45	.44	.45	.50	.55	.58	.59	30	.27	.33	.24	.40	.40	.39
5	FS1					-	.60	.65	.42	.29	.34	.25	.35	.40	.12	.19	.17	.21	.17	.18	.17
6	FS2						-	.64	.56	.47	.47	.36	.49	.52	.18	.22	.26	.17	.26	.29	.30
7	FS3							-	.50	.46	.45	.33	.42	.49	.18	.25	.21	.17	.21	.19	.18
8	AS1								-	.67	.72	.52	.63	.64	.23	.23	.26	.28	.35	.35	.37
9	AS2									-	.80	.59	.61	.57	.23	.20	.29	.25	.42	.38	.38
10	AS3										-	.57	.68	.63	.29	.25	.36	.32	.46	.44	.44
11	RLX1											-	.76	.69	.38	.28	.41	.21	.51	.48	.50
12	RLX2												-	.75	.38	.28	.41	.26	.50	.51	.54
13	RLX3													-	.39	.34	.46	.24	.42	.42	.45
14	ATT1														-	.55	.59	*.10*	.23	.24	.24
15	ATT2															-	.37	*.08*	.18	.17	.18
16	ATT3																-	*.10*	.22	.21	.22
17	SN																	-	.49	.48	.45
18	INT1																		-	.94	.92
19	INT2																			-	.95
20	INT3																				-

Note. Significant at $p < .05$, non-significant correlations are in Italic. NOV = novelty, FS = fashion/status, AS = affection/sociability, RLX = relaxation, ATT = attitude, SN = subjective norm, INT = intention.

Table 7.7

Descriptive Statistics, Factor Loadings, Squared Multiple Correlations, and Cronbach's Alpha of the Observed Indicators to Predict Mobile Video Phone Intention

	M	*SD*	β	R^{2b}
Behavioral intention (α = .98)				.22
I intend to use mobile video phone in the next three months	1.71	1.40	.93	.86
I predict I would use mobile video phone in the next three months	1.69	1.33	.99	.99
I plan to use mobile video phone in the next three months	1.64	1.32	.98	.97
Attitude (α = .75)				.30
Extremely unpleasant/pleasant	3.32	1.26	.85	.72
Extremely unimportant/important	3.36	1.29	.62	.39
Extremely harmful/beneficial	3.67	1.37	.70	.48
Novelty (α = .84)[a]				.89
To try out something new	3.87	5.98	.76	.58
Because it's something new	3.39	5.74	.86	.74
To communicate in a new way	2.04	6.16	.69	.47
Because it adds something new	3.47	5.39	.75	.56
Fashion/Status (α = .83)[a]				.40
To have it as a status symbol	.67	2.87	.76	.57
To look stylish	.73	3.27	.79	.63
To distinguish myself from others	.64	3.13	.83	.69
Affection/Sociability (α = .89)[a]				.70
To strengthen my relationship with family and friends	1.13	4.57	.79	.63
To maintain contact with family and friends	1.99	5.27	.87	.75
To keep my family and friends informed	2.03	5.07	.92	.84
Relaxation (α = .89)[a]				.96
To have fun	3.46	5.71	.83	.69
To enjoy	2.78	5.26	.90	.81
To have a pleasant conversation	2.24	5.18	.84	.71
Subjective norm	2.27	1.48		

Note. [a]The means and standard deviations of expectancy-value judgments are for 37 point scales (-18 to +18) formed from the product of two seven point scales: evaluations ranging from -3 = "extremely bad feature" to +3 = "extremely good feature", and beliefs ranging from 0 = "definitely does not have feature" to 6 = "definitely does have feature".

[b]The R^2 of a latent dependent predictor is the percent of the variance in the latent dependent variable accounted for by the latent independent variable. The R^2 of an observed indicator is the estimated percent variance explained in that variable. In other words, the error variance of a variable is approximately 1 minus the percent of the variance of the variable itself.

7.3 Model of Media Attendance

To empirically test the model of media attendance in the context of mobile communication technology, both the measurement and structural model of the media attendance model were developed to successively explain mobile phone use and to predict mobile video phone adoption.

The original items by LaRose and Eastin (2004) to explain Internet usage were rephrased in the context of mobile communication technology use and adoption. Substituted items were collected from prior mobile communication technology studies (i.e., Peters & Ben Allouch, 2005; Peters et al., 2006) and classified in accordance with the conceptual definitions found in Bandura (1986).

Pre-test. Under-graduate students ($N = 62$) from both the departments of Communication Studies and Psychology at the University of Twente in the Netherlands participated in a pre-test of the model of media attendance for research experience points. The rephrased items were pre-tested on legibility and internal consistency. Furthermore, items with highly correlated error variances and items that loaded poorly onto its unique factor were removed. This procedure resulted in a reduction of the number of observed indicators of the latent constructs. As result of the pre-test, additional items to explain mobile phone use were developed to have a stronger operationalization of the expected outcome measures novel ($\alpha = .50$) and status ($\alpha = .51$). The internal consistency of the other measures to explain mobile phone and the measures to predict mobile video use was above aspiration level ($\alpha > .70$).

7.3.1 Measures

Mobile phone behavior and experience. To measure mobile phone use, respondents were asked to estimate the number of times they used a mobile phone to make a phone call on an average weekday, and similarly respondents were asked to estimate the number of times they used a mobile phone to send a SMS message on an average week day. Mobile phone experience was measured in years the respondents had used a mobile phone.

Expected outcomes. In the context of mobile phone use, expected outcomes (i.e., "using a mobile phone how likely are you to ___") were measured on a

Likert-type scale that ranged from 1 (*very unlikely*) to 7 (*very likely*). The expected outcomes measures include monetary incentives, social incentives, status incentives, novel incentives, activity, and self-reactive incentives (see Table 7.9). Although the operationalization of monetary incentives are in terms of benefit and profit (e.g., saving time, do a better job) rather then in terms of money, for the sake of distinctness in this study the same labels for the incentives are used as originally defined in Bandura (1986).

Self-efficacy, habit strength, and deficient self-regulation. Self-efficacy (e.g., "I can handle my mobile phone without the help from others"), habit strength (e.g., "The use of a mobile phone is part of my daily routine"), and deficient self-regulation (e.g., I have a hard time keeping my mobile phone use under control) were measured on a Likert-type scale that ranged from 1 (*fully disagree*) to 7 (*fully agree*). Table 7.9 summarizes the items of the three measures.

Mobile video phone measures. In the context of mobile video phone adoption, expected outcomes, self-efficacy, and mobile phone experience were measured similar as in the context of mobile phone use (see Table 7.11). Since mobile video telephony is a new technology, it is not likely that this new technology has already been habitualized. Therefore, habit strength is operationalized in terms of forethought; for example, the habit strength item 'The use of a mobile phone is part of my daily routine' is modified into the prospective habit strength item 'The use of mobile video phone would be a part of my daily routine'. Deficient self-regulation (e.g., 'I have tried unsuccessfully to cut down the amount of time I spend using my mobile phone') was not included in the instrument to measure intention of mobile video phone adoption because a valid judgment about deficient self-regulation would in contrast to prospective habit strength imply that respondents should have had experience with mobile video phone.

Behavioral intention to use mobile video phone. Behavioral intention (e.g., "I intend to use mobile video phone within the next 6 months") was measured with three items (see table 7.11) on a Likert-type scale that ranged from 1 (*fully disagree*) to 7 (*fully agree*).

7.3.2 Explaining Mobile Phone Use

Prior to the analyses, data were checked for normality. Because of skewness to the upper end of the distribution of the measures mobile phone usage, SMS usage, and deficient self-regulation, a square-root transformation was performed to correct skew. Because of skewness to the lower end of the distribution of the measure self-efficacy, an inverse (reciprocal) transformation was performed to correct skew (Garson, 2006).

Using a first-order confirmatory factor analysis, the measurement model estimated the extent to which the observed items loaded onto their respective latent variables. Because experience was measured with a single observed item, it was not included in the measurement model. All latent constructs but no observed error variances were allowed to co-vary with one another.

Measurement model. The initial measurement model generated a poor fit, $\chi^2(876) = 2546.21$, $\chi^2/df = 2.91$, SRMR = .113, TLI = .814, RMSEA = .076 (CI: .72, .79). An inspection of the observed items showed that the items of both novel and social outcomes loaded poorly onto its unique factor. The internal consistency of the measures novel outcomes ($\alpha = .53$) and status outcomes ($\alpha = .61$) was below aspiration level ($\alpha > .70$). This procedure resulted that both novel outcomes and status outcomes were excluded to better fit the measurement model. The modified measurement model of model of media attendance generated an adequate fit, $\chi^2(202) = 410.35$, $\chi^2/df = 2.03$, SRMR = .053, TLI = .949, RMSEA = .056 (CI: .048, .063). The internal consistency of the measures to explain mobile phone use was above aspiration level ($\alpha > .70$). The correlation matrix of the observed variables, mobile phone usage, and SMS usage is shown in Table 7.8.

Structural model. The results obtained from testing the validity of a causal structure of the hypothesized model showed that the initial model did not fit the data well, $\chi^2(239) = 672.44$, $\chi^2/df = 2.81$, SRMR = .137, TLI = .904, RMSEA = .074 (CI: .067, .080), AIC = 794.44, ECVI = 2.39 (CI: .2.17, 2.63). In testing the original model to explain Internet usage, LaRose and Eastin (2004) added several correlated error terms suggested by post hoc modification indices to improve model fit. An inspection of the modification indices of the structural model to explain mobile communication technology use suggested an improved fit by correlating the error terms of habit strength with monetary outcomes ($r =$

.64); and self-reactive outcomes with both activity outcomes (r = .73) and deficient self-regulation (r = .33). The respecified model generated an adequate fit, $\chi^2(236) = 521.89$, $\chi^2/df = 2.21$, SRMR = .102, TLI = .936, RMSEA = .060 (CI: .053, .067), AIC = 649.89, ECVI = 1.95 (CI: .1.77, 2.16). Table 7.9 summarizes the original (uncorrected) mean and standard deviation, Cronbach's α, the factor loading (β), and the squared multiple correlation (R^2) of the observed indicators to explain mobile phone use.

Path model. The path model with standardized path coefficients is featured in Figure 7.5. The standardized path coefficients in Figure 7.5 show a significant direct effect of habit strength and deficient self-regulation on mobile phone usage, and non-significant direct effects of expected outcomes and self-efficacy on mobile phone usage. Also Figure 7.5 shows significant direct effects of outcome expectations, self-efficacy, and deficient self-regulation on habit strength, and a significant direct effect of experience on self-efficacy. Activity and social outcomes were the strongest contributors of expected outcomes followed by self-reactive and monetary outcomes. The direct effect of self-efficacy on expected outcomes and experience on habit strength were not significant. The indirect effect of expected outcomes on mobile phone usage (β = .34) is mediated by the direct effect of outcome expectations on habit strength. Also, the indirect effect of self-efficacy (β = .09) and deficient self regulation (β = .50) on mobile phone usage is mediated by the direct effect on habit strength. The indirect effect of experience on mobile phone usage (β = .01) is mediated via the consecutive effect of self-efficacy and habit strength on mobile phone use. Squared multiple correlations provide information about the variance accounted for by the complete set of variables and showed that mobile phone use was accounted for 76% (see Table 7.9).

Table 7.8

Correlation Matrix of the Observed Variables, Mobile Phone Usage, and SMS Usage

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1	SR1	-	.76	.73	.39	.42	.52	*.09*	.15	.12	.61	.60	.71	.29	.21	.35	*.04*	*.05*	*.06*	.44	.39	.34	*.02*	*.08*	*.11*
2	SR2		-	.74	.38	.41	.48	.08	.13	*.08*	.59	.60	.70	.25	.18	.36	*.05*	*.05*	*.05*	.42	.40	.40	*.00*	*.06*	*.08*
3	SR3			-	.35	.39	.48	.13	.17	.16	.55	.56	.67	.29	.25	.40	*.09*	*.11*	*.08*	.45	.38	.41	*.02*	.16	.23
4	SOC1				-	.73	.62	.19	.34	.19	.54	.52	.53	.36	.16	.34	*.10*	*.08*	*.09*	.24	.21	.18	*.07*	*.03*	.13
5	SOC2					-	.63	.18	.36	.22	.54	.60	.61	.40	.20	.37	*.09*	*.07*	*.10*	.27	.23	.18	*.05*	*.09*	.14
6	SOC3						-	.17	.26	.15	.58	.55	.60	.29	.12	.32	*.03*	*.01*	*.01*	.34	.30	.24	*.07*	*.04*	.16
7	MON1							-	.49	.60	.24	.21	.18	.45	.45	.49	*.06*	*.01*	*.01*	*.11*	*.10*	.14	.17	.17	*.08*
8	MON2								-	.70	.30	.28	.26	.45	.33	.47	*.10*	.13	*.10*	*.05*	*.03*	*.05*	.13	.15	*.07*
9	MON3									-	.19	.21	.17	.46	.42	.49	*.03*	*.06*	*.06*	*.06*	*.04*	*.10*	.17	.15	*.06*
10	ACT1										-	.71	.74	.35	.28	.39	*.01*	*.05*	*.04*	.30	.26	.26	*.03*	*.06*	*.09*
11	ACT2											-	.78	.37	.30	.46	*.11*	*.10*	*.09*	.35	.30	.28	*.03*	*.08*	.17
12	ACT3												-	.40	.31	.42	*.10*	*.08*	*.07*	.42	.34	.32	*.01*	*.05*	.21
13	HS1													-	.61	.67	.12	.13	*.09*	.32	.30	.32	.17	.18	*.10*
14	HS2														-	.63	.17	.26	.20	.15	.11	.15	*.08*	.17	*.09*
15	HS3															-	.18	.16	.15	.23	.21	.21	.12	.34	.15
16	SE1																-	.64	65	*.01*	*.07*	*.06*	*.09*	*.03*	*.05*
17	SE2																	-	.84	*.02*	*.01*	*.02*	*.11*	*.05*	*.06*
18	SE3																		-	*.03*	*.02*	*.02*	.15	*.04*	*.06*
19	DSR1																			-	.76	.70	*.01*	.24	.34
20	DSR2																				-	.84	*.03*	.27	.26
21	DSR3																					-	*.04*	.33	.26
22	EXP																						-	.29	*.04*
23	PHONE																							-	.14
24	SMS																								-

Note. Correlations significant at $p < .05$, non-significant correlations are in Italic. SR = self-reactive, SOC = social, MON = monetary, ACT = Activity, HS = habit strength, SE = self-efficacy, DSR = deficient self-regulation, exp = experience, PHONE = mobile phone use, SMS = SMS use.

Table 7.9

Descriptive Statistics, Factor Loadings, Squared Multiple Correlations, and Cronbach's Alpha of the Observed Indicators to Explain Mobile Phone Use

	M	*SD*	β	R^2
Usage				.76
Mobile phone (*typical weekday*)	3.29	5.64	.52	.28
SMS (*typical weekday*)	1.72	2.68	.48	.23
Social outcomes (α = .85)				.72
To keep my family and friends up-to-date	3.96	2.08	.82	.67
To keep up contact with my family and friends	3.95	2.07	.86	.74
To strengthen my relations with family and friends	3.34	1.99	.76	.58
Activity outcomes (α = .90)				.86
Because I like to be called	2.97	2.00	.82	.67
To have a nice conversation	2.93	2.01	.85	.73
Because it's a pleasant activity	2.46	1.75	.92	.84
Monetary outcomes (α = .81)				.12
To save time because I am accessible everywhere	4.74	2.11	.69	.48
To be more quickly accessible	5.31	1.89	.78	.62
To be always accessible	5.74	1.72	.87	.76
Self-reactive outcomes (α = .89)				.43
To relax	1.87	1.37	.86	.74
To pass the time	1.82	1.38	.86	.74
When I don't have anything to do	2.20	1.64	.82	.68
Novel outcomes (α = .53)				
To get immediate knowledge of the latest news	2.05	1.53		
To take pictures	2.40	1.84		
To send text-messages	4.14	2.23		
Status outcomes (α = .61)				
Fits my lifestyle	2.73	1.88		
Because it is a modern way to communicate	3.34	2.02		
Get up to date with new technology	2.34	1.63		
Self-efficacy (α = .92)				.02
I can handle my mobile phone without the help from others	6.57	1.02	.78	.61
It is no problem for me to operate my mobile phone	6.56	.95	.97	.94
I have the knowledge and skills to operate my mobile phone	6.56	.94	.93	.86
Habit strength (α = .84)				.33
The use of a mobile phone is part of my daily routine	4.36	2.15	.88	.78
I always carry my mobile phone with me	5.66	1.74	.70	.49
I would miss a mobile phone if it would not be available	5.08	1.94	.76	.58
Deficient self-regulation (α = .90)				.00
I have a hard time keeping my mobile phone use under control	1.65	1.25	.89	.79
I feel my mobile phone use get out of hand	1.54	1.17	.95	.89
I have tried unsuccessfully to cut down the amount of time I spend using my mobile phone	1.58	1.26	.81	.65
Mobile phone experience	6.90	2.84		

Note. The R^2 of a latent dependent predictor is the percent of the variance in the latent dependent variable accounted for by the latent independent variable. The R^2 of an observed indicator is the estimated percent variance explained in that variable. In other words, the error variance of a variable is approximately 1 minus the percent of the variance of the variable itself.

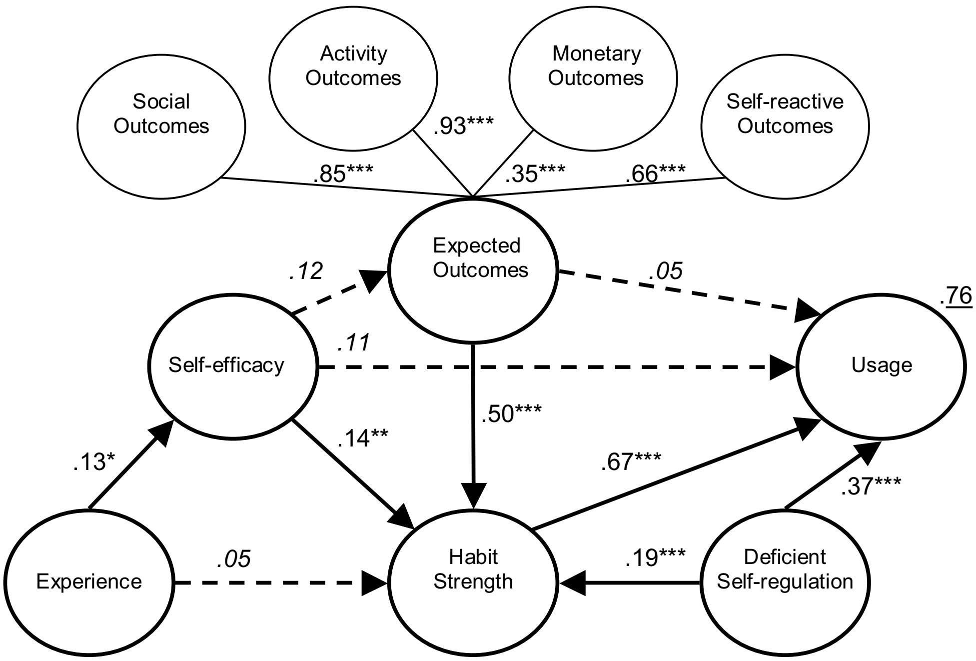

Figure 7.5. Standardized path coefficients of the model of media attendance to explain mobile phone use. The observed indicators of the latent construct are not shown (see Table 7.9).

Note. *$p < .05$, **$p < .01$, ***$p < .001$. Dotted lines are non-significant paths (non-significant factor loadings in Italic). Squared multiple correlations are underlined.

7.3.3 Predicting Mobile Video Phone Adoption

Prior to the analyses, data were checked for normality. Because of skewness to the lower end of the distribution of the mobile video phone measures (expect for self-efficacy), an inverse (reciprocal) transformation was performed to correct skew (Garson, 2006).

Using a first-order confirmatory factor analysis, the measurement model estimated the extent to which the observed items loaded onto their respective latent variables. Because experience was measured with a single observed item, it was not included in the measurement model. All latent constructs but no observed error variances were allowed to co-vary with one another.

Measurement model. The measurement model of the model of media attendance generated an adequate fit, $\chi^2(168) = 397.84$, $\chi^2/df = 2.37$, SRMR = .032, TLI = .961, RMSEA = .067 (CI: .058, .075). The internal consistency of the measures to predict mobile video phone adoption was above aspiration level ($\alpha > .70$). The correlation matrix of the observed variables and mobile video phone intention is shown in Table 7.10. The correlation matrix shows that the indicators of activity are closely related to the indicators of status.

Structural model. The results obtained from testing the validity of a causal structure of the hypothesized model showed a good fit, $\chi^2(337) = 834.00$, $\chi^2/df = 2.48$, SRMR = .040, TLI = .948, RMSEA = .069 (CI: .063, .075), AIC = 972.00, ECVI = 3.15 (CI: 2.88, 3.43). Table 7.11 summarizes the original (uncorrected) mean and standard deviation, Cronbach's α, the factor loading (β), and the squared multiple correlation (R^2) of the observed indicators to predict mobile video phone adoption.

Path model. The path model with standardized path coefficients is featured in Figure 7.6. The standardized path coefficients in Figure 7.6 show significant direct effects of expected outcomes and prospective habit strength on mobile video phone intention. The direct effect of self-efficacy on mobile video phone intention is not significant. Figure 7.6 also show significant direct effects of expected outcomes on prospective habit strength, mobile phone experience on self-efficacy, and self-efficacy on expected outcomes. The direct effects of self-efficacy and experience on prospective habit strength are not significant. Activity, status, and monetary outcomes were the strongest contributors to the latent construct expected outcomes followed by social, novel, and self-reactive outcomes. Although the direct effect of prospective habit strength on mobile video phone intention is stronger than the effect of expected outcomes, the total effect of expected outcomes (β = .58) on mobile video phone intention surpasses the direct effect of prospective habit strength. Further total effects on mobile video phone intention were expected self-efficacy (β = .10) and mobile phone experience (β = .02). Furthermore, there were significant total effects of mobile phone experience (β = .03) and self-efficacy (β = .12) on prospective habit strength, and a significant total effect of mobile phone experience (β = .04) on expected outcomes. Squared multiple correlations provide information about the variance accounted for by the complete set of variables and showed that mobile video phone intention was accounted for 41% (see Table 7.11).

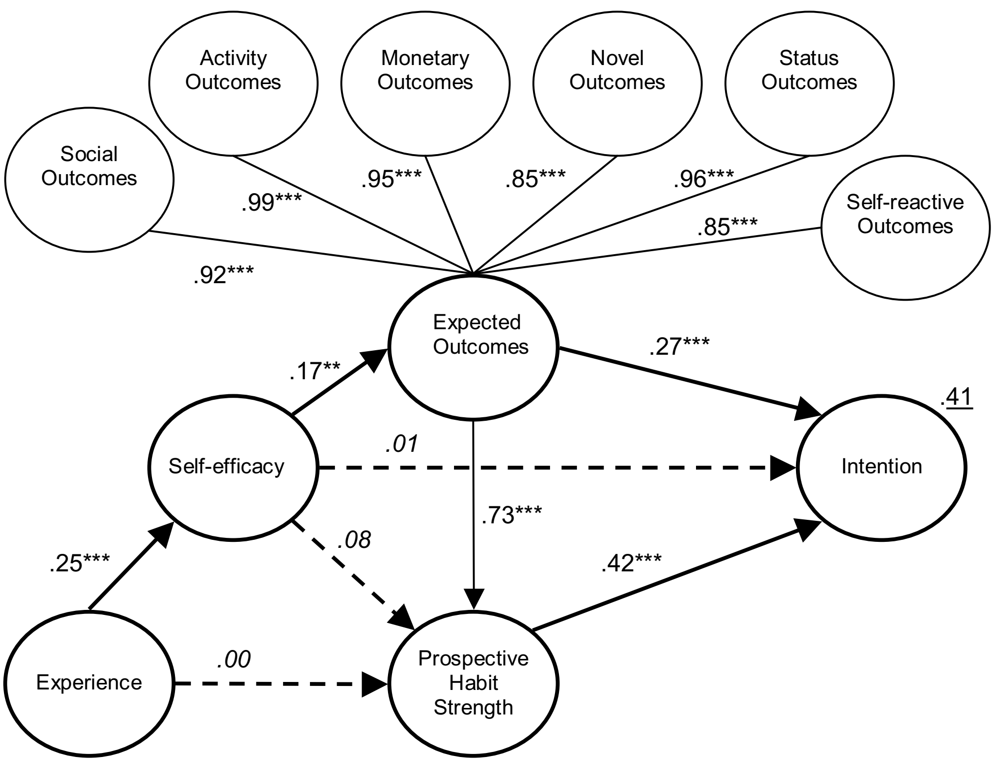

Figure 7.6. Standardized path coefficients of the model of media attendance to predict mobile video phone adoption. The observed indicators of the latent construct are not shown (see Table 7.11).

Note. $^{**}p < .01$, $^{***}p < .001$. Dotted lines are non-significant paths (non-significant factor loadings in Italic). Squared multiple correlations are underlined.

Table 7.10

Correlation Matrix of the Observed Variables, and Mobile Video Phone Intention

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
1	SR1	-	.79	.74	.50	.47	.49	.47	.52	.49	.53	.64	.65	.55	.47	.52	.53	.57	.53	.31	.31	.44	.18	.14	.15	*.07*	.30	.30	.30
2	SR2		-	.85	.62	.52	.57	.53	.55	.52	.52	.63	.60	.53	.47	.50	.54	.54	.51	.38	.43	.52	.13	*.11*	.13	*.07*	.34	.34	.32
3	SR3			-	.65	.55	.56	.55	.55	.51	.52	.65	.64	.50	.48	.47	.50	.50	.50	.42	.47	.51	.13	*.10*	.14	*.05*	.31	.32	.30
4	SOC1				-	.76	.66	.55	.57	.56	.63	.62	.64	.58	.53	.60	.51	.55	.53	.45	.44	.53	.15	.15	.17	*.08*	.32	.34	.34
5	SOC2					-	.69	.52	.61	.55	.64	.56	.63	.56	.46	.61	.56	.58	.52	.49	.43	.53	.16	.15	.17	*.05*	.33	.33	.30
6	SOC3						-	.52	.55	.57	.66	.56	.61	.58	.46	.57	.60	.55	.47	.40	.40	.48	.16	.16	.17	*.08*	.31	.29	.27
7	MON1							-	.78	.70	.66	.68	.65	.51	.48	.61	.66	.56	.62	.48	.41	.49	.17	.17	.20	*.01*	.33	.32	.29
8	MON2								-	.72	.69	.65	.68	.54	.49	.58	.60	.63	.59	.53	.49	.52	.19	.16	.20	*.03*	.42	.42	.39
9	MON3									-	.68	.57	.71	.52	.48	.55	.54	.66	.61	.47	.45	.47	.13	.12	.15	*.04*	.39	.39	.37
10	ACT1										-	.73	.74	.62	.60	.64	.65	.66	.63	.43	.42	.49	.23	.20	.22	*.13*	.44	.42	.41
11	ACT2											-	.82	.62	.58	.65	.66	.70	.67	.40	.39	.51	.16	.12	.14	*.04*	.41	.40	.40
12	ACT3												-	.65	.61	.62	.62	.77	.63	.49	.45	.54	.17	.16	.17	*.03*	.44	.43	.42
13	NOV1													-	.77	.80	.50	.55	.53	.37	.37	.41	.16	.11	.15	*.02*	.33	.35	.33
14	NOV2														-	.67	.45	.55	.52	.29	.30	.33	.19	.17	.18	*.06*	.34	.33	.32
15	NOV3															-	.55	.55	.54	.37	.39	.42	.15	.13	.15	*.03*	.34	.35	.33
16	STAT1																-	.63	.62	.54	.48	.53	*.10*	*.09*	.11	*.11*	.48	.42	.42
17	STAT2																	-	.74	.46	.47	.56	.13	.12	.14	.14	.51	.40	.40
18	STAT3																		-	.48	.46	.50	.21	.16	.20	.14	.50	.38	.40
19	HS1																			-	.72	.73	*.10*	*.04*	*.07*	*.04*	.48	.48	.46
20	HS2																				-	.83	*.04*	*.01*	*.05*	*.05*	.48	.49	.46
21	HS3																					-	*.08*	*.07*	*.09*	*.06*	.45	.48	.45
22	SE1																						-	.79	.76	.19	.12	*.11*	.12
23	SE2																							-	.92	.23	*.08*	*.08*	*.09*
24	SE3																								-	.24	.12	*.11*	*.11*
25	EXP																									-	*.05*	*.06*	*.06*
26	INT1																										-	.94	.91
27	INT2																											-	.96
28	INT3																												-

Note. Correlations significant at $p < .05$, non-significant correlations are in Italic. SR = self-reactive, SOC = social, MON = monetary, ACT = Activity, NOV = novel, STAT = status, HS = habit strength, SE = self-efficacy, EXP = experience, INT = intention.

Table 7.11

Descriptive Statistics, Factor Loadings, Squared Multiple Correlation, and Cronbach's Alpha of the Observed Indicators to Predict Mobile Video Phone Adoption

	M	*SD*	β	R^2
Behavioral intention (α = .98)				.40
I plan to use mobile video phone within the next 6 months	1.47	1.08	.98	.96
I intend to use mobile video phone within the next 6 months	1.43	1.02	.98	.96
I will use mobile video phone within the next 6 months	1.39	.96	.95	.91
Social outcomes (α = .89)				.86
To keep my family and friends up-to-date	2.09	1.57	.83	.70
To keep up visual contact with family and friends	2.01	1.63	.87	.76
To strengthen my relations with family and friends	1.75	1.41	.87	.75
Activity outcomes (α = .91)				.96
Because of the possibility to call with video	2.49	1.89	.85	.73
To have a nice conversation	2.22	1.78	.90	.81
Because it's a pleasant activity	2.07	1.62	.87	.77
Monetary outcomes (α = .91)				.91
To communicate in a more understandable manner	2.33	1.78	.86	.74
To not just have to communicate with voice only	2.10	1.68	.91	.82
To better communicate	2.10	1.63	.86	.75
Novel outcomes (α = .89)				.73
To capture video clips	2.31	1.82	.93	.87
To take pictures	2.90	2.06	.81	.66
To send video clips	2.16	1.69	.89	.79
Status outcomes (α = .85)				.92
Fits my lifestyle	1.66	1.29	.77	.59
Because it is a modern way to communicate	2.20	1.78	.86	.74
Get up to date with new technology	2.33	1.79	.84	.71
Self-reactive outcomes (α = .95)				.72
To relax	1.64	1.19	.94	.89
To pass the time	1.58	1.13	.95	.90
When I don't have anything to do	1.72	1.35	.92	.84
Self-efficacy (α = .95)				.06
I would handle mobile video phone without the help from others	4.70	2.25	.81	.65
It would be no problem for me to operate mobile video phone	5.17	2.02	.98	.96
I have the knowledge and skills to operate mobile video phone	5.21	2.04	.94	.89
Prospective habit strength (α = .91)				.51
The use of mobile video phone would be part of my daily routine	1.58	.96	.80	.64
I would always make phone calls with mobile video phone	1.48	1.02	.92	.84
I would miss mobile video phone if it would not be available	1.54	1.10	.92	.85
Mobile phone experience	6.90	2.84		

Note. The R^2 of a latent dependent predictor is the percent of the variance in the latent dependent variable accounted for by the latent independent variable. The R^2 of an observed indicator is the estimated percent variance explained in that variable. In other words, the error variance of a variable is approximately 1 minus the percent of the variance of the variable itself.

7.4 Unified Model of Acceptance and Use of Technology

To empirically test the unified model of acceptance and use of technology, both the measurement and structural model of the unified model acceptance and use of technology were developed to successively explain mobile phone use and to predict mobile video phone adoption.

The original items by Venkatesh et al. (2003) were rephrased in the context of mobile communication technology use and adoption.

Pre-test. Under-graduate students (N= 62) from both the departments of communication studies and psychology at the University of Twente in the Netherlands participated in a pre-test of the unified model of acceptance and use of technology for research experience points. Furthermore, items with highly correlated error variances and items that loaded poorly onto its unique factor were removed. This procedure resulted in a reduction of the number of observed indicators of the latent constructs. The rephrased items were pre-tested on legibility and internal consistency. As result of the pre-test, additional items to explain mobile phone use were developed to have a stronger operationalization of the facilitation conditions measure ($\alpha < .70$). The internal consistency of the other measures to explain mobile phone and the measures to predict mobile video use was above aspiration level ($\alpha > .70$).

7.4.1 Measures

Mobile phone behavior. Respondents were asked to estimate the number of times they used a mobile phone to make a phone call on an average weekday. Similarly respondents were asked to estimate the number of times they used a mobile phone to send a SMS message on an average week day.

Behavioral intention. Three intention measures asked the respondents to rate their intention to use a mobile phone in the next week on a seven-point bipolar scale ranging from 1 (*extremely unlikely*) to 7 (*extremely likely*). The three intention measures were: ‘I plan to use a mobile phone in the next week’, ‘I predict I would use a mobile phone in the next week’, and ‘I intend to use a mobile phone in the next week’.

Behavioral intention to use mobile video phone. Behavioral intention was measured with three items on a Likert-type scale that ranged from 1 (*fully disagree*) to 7 (*fully agree*). The three intention measures were: 'I plan to use mobile video telephony in the next three months', 'I predict I would use mobile video telephony in the next three months', 'I intend to use mobile video telephony in the next three months'.

Performance expectancy, e*ffort expectancy, social influence, and facilitating conditions.* In the context of mobile phone use, performance expectancy, effort expectancy, social influence, and facilitating conditions were measured (see Table 7.13) on a Likert-type scale that ranged from1 (*fully disagree*) to 7 (*fully agree*). Performance expectancy, effort expectancy, social influence, and mobile phone experience were measured likewise (see Table 7.15) in the context of mobile video phone adoption.

7.4.2 Explaining Mobile Phone Use

Prior to the analyses, data were checked for normality. Because of skewness to the upper end of the distribution of the measures mobile phone usage and SMS usage, a square-root transformation was performed to correct skew (Garson, 2006).

Using a first-order confirmatory factor analysis, the measurement model estimated the extent to which the observed items loaded onto their respective latent variables. All latent constructs but no observed error variances were allowed to co-vary with one another.

Measurement model. The initial measurement model generated an adequate fit, $\chi^2(142) = 362.68$, $\chi^2/df = 2.55$, SRMR = .069, TLI = .919, RMSEA = .070 (CI: .61, .79). An inspection of the observed items showed that the items of facilitating conditions loaded poorly onto its unique factor. The internal consistency of the measure facilitating conditions ($\alpha = .38$) was below aspiration level ($\alpha > .70$). This procedure resulted that facilitating conditions was excluded from the measurement model. The modified measurement model of the unified model of acceptance and use of technology generated a good fit, $\chi^2(67) = 120.47$, $\chi^2/df = 1.80$, SRMR = .038, TLI = .970, RMSEA = .050 (CI: .035, .064). The correlation matrix of the observed variables, mobile phone usage, and SMS usage is shown in Table 7.12. The internal consistency of the measures to explain mobile phone use was above aspiration level (α > .70),

Table 7.12

Correlation Matrix of the Observed Variables, Mobile Phone Usage, and SMS Usage

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	PE1	-	.52	.53	.41	.23	.24	*.08*	*.11*	.14	.40	.43	.45	.27	.13
2	PE2		-	.54	.41	.32	.31	.14	.14	.18	.48	.55	.52	.36	.20
3	PE3			-	.38	.33	.37	*.08*	*.10*	.13	.33	.36	.36	.32	.20
4	EE1				-	.46	.58	*.03*	*.07*	*.03*	.27	.29	.32	.21	.20
5	EE2					-	.46	*.08*	*.06*	*.02*	.12	.15	.19	.12	.13
6	EE3						-	*.05*	*.02*	*.10*	.25	.29	.32	.16	.15
7	SI1							-	.67	.73	*.09*	*.05*	*.09*	*.01*	*.03*
8	SI2								-	.86	*.04*	*.01*	*.06*	.12	*.05*
9	SI3									-	*.09*	*.05*	*.11*	*.09*	*.07*
10	INT1										-	.86	.81	.29	.20
11	INT2											-	.85	.29	.20
12	INT3												-	.31	.24
13	PHONE													-	.22
14	SMS														-

Note. Correlations significant at $p < .05$, non-significant correlations are in Italic.

Structural model. The results obtained from testing the validity of a causal structure of the hypothesized model showed that the initial model did not fit the data, $\chi^2(73) = 154.99$, $\chi^2/df = 3.49$, SRMR = .140, TLI = .907, RMSEA = .088 (CI: .077, .100), AIC = 318.99, ECVI = 1.00 (CI: .86, 1.16). In contrast to Venkatesh et al. (2003) test of the original unified model of acceptance and use of technology, post hoc modification indices suggested an improved fit of the unified model to explain mobile communication technology use by adding a path from effort expectancy to performance expectancy. The respecified model generated a good fit, $\chi^2(72) = 163.63$, $\chi^2/df = 2.27$, SRMR = .071, TLI = .953, RMSEA = .063 (CI: .050, .076), AIC = 229.63, ECVI = .72 (CI: .62, .85). Table 7.13 summarizes the original (uncorrected) mean and standard deviation, Cronbach's α, the factor loading (β), and the squared multiple correlation (R^2) of the observed indicators to explain mobile phone use.

Path model. The path model with standardized path coefficients is featured in Figure 7.7. The standardized path coefficients in Figure 7.7 show a significant direct effect of behavioral intention on mobile phone usage. Also Figure 7.7 show a significant direct effect of performance expectancy on behavioral intention, and a non-significant direct effect of effort expectancy and social influence on behavioral intention. The significant indirect effect of effort expectancy on behavioral intention (β = .47) is mediated by the significant direct effect of effort expectancy on performance expectancy. The significant indirect of effort expectancy on mobile phone usage (β = .33) is mediated via performance expectancy and behavioral intention. Squared multiple correlations provide information about the variance accounted for by the complete set of variables and showed that behavioral intention was accounted for 46% and mobile phone use was accounted for 48% (see Table 7.13).

Table 7.13

Descriptive Statistics, Factor Loadings, Squared Multiple Correlations, and Cronbach's Alpha of the Observed Indicators to Explain Mobile Phone Use

	M	*SD*	β	R^2
Usage				.48
Mobile phone (*typical weekday*)	3.42	4.76	.67	.45
SMS (*typical weekday*)	1.71	3.00	.53	.28
Performance expectancy (α = .77)				.42
I find a mobile phone useful in my daily life	5.85	1.38	.70	.48
Using a mobile phone enables me to accomplish tasks more quickly	5.59	1.58	.79	.62
I find benefit in using a mobile phone	5.42	1.57	.69	.48
Effort expectancy (α = .75)				.00
I find a mobile phone easy to use	5.46	1.55	.81	.65
To operate a mobile phone is no problem for me	5.94	1.40	.59	.35
Learning to use a mobile phone is easy for me	5.74	1.31	.72	.52
Social influence (α = .90)				.00
People who influence my behavior think I should use a mobile phone	2.74	1.95	.75	.56
People who are important to me think that I should use a mobile phone	3.47	2.05	.89	.79
People whose opinion I value think I should use a mobile phone	3.34	2.06	.97	.94
Facilitating Conditions (α = .38)				
I have the resources necessary to use a mobile phone	4.66	2.06		
I have the knowledge necessary to use a mobile phone	1.79	1.14		
A specific person is available for assistances with mobile phone difficulties	3.06	1.81		
Behavioral Intention (α = .94)				.46
I plan to use a mobile phone in the next week	5.81	1.93	.90	.81
I predict I would use a mobile phone in the next week	5.97	1.82	.94	.89
I intend to use a mobile phone in the next week	5.95	1.87	.91	.82

Note. The R^2 of a latent dependent predictor is the percent of the variance in the latent dependent variable accounted for by the latent independent variable. The R^2 of an observed indicator is the estimated percent variance explained in that variable. In other words, the error variance of a variable is approximately 1 minus the percent of the variance of the variable itself.

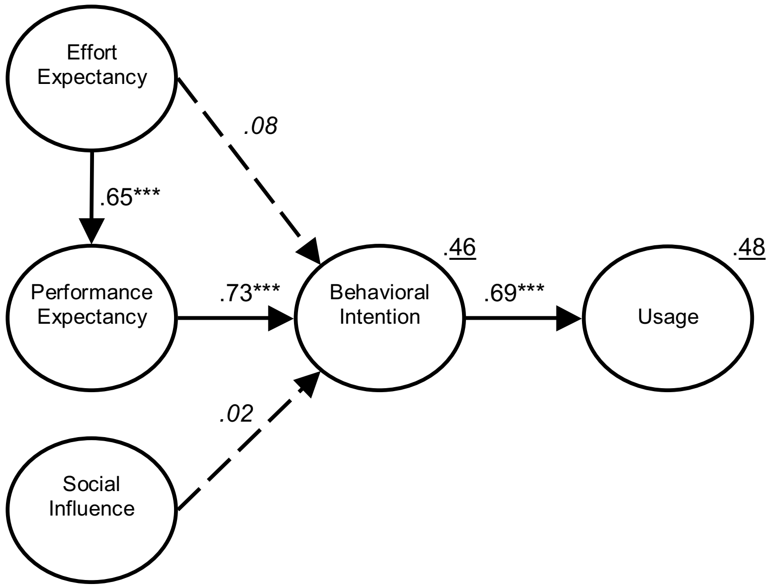

Figure 7.7. Standardized path coefficients of the unified model of acceptance and use of technology to explain mobile phone use. The observed indicators of the latent construct are not shown (see Table 7.13).
Note. ***$p < .001$. Dotted lines are non-significant paths (non-significant factor loadings in Italic). Squared multiple correlations are underlined.

7.4.3 Predicting Mobile Video Phone Adoption

Prior to the analyses, data were checked for normality. Because of skewness to the lower end of the distribution of the measure mobile video phone, an inverse (reciprocal) transformation was performed to correct skew (Garson, 2006).

Using a first-order confirmatory factor analysis, the measurement model estimated the extent to which the observed items loaded onto their respective latent variables. All latent constructs but no observed error variances were allowed to co-vary with one another.

Measurement model. The measurement model of the unified model of acceptance and use of technology generated a good fit, $\chi^2(48) = 77.49$, $\chi^2/df = 1.61$, SRMR = .037, TLI = .986, RMSEA = .043 (CI: .024, .060). The internal consistency of the measures to predict mobile video phone adoption was above aspiration level (α > .70). The correlation matrix of the observed variables and mobile video phone intention is shown in Table 7.14.

Structural model. The results obtained from testing the validity of a causal structure of the hypothesized model showed a poor fit, $\chi^2(51) = 201.29$, $\chi^2/df = 3.95$, SRMR = .174, TLI = .933, RMSEA = .094 (CI: .081, .108), AIC = 255.29, ECVI = .77 (CI.: .65, .91). In contrast to Venkatesh et al. (2003) test of the original unified model of acceptance and use of technology, post hoc modification indices suggested an improved fit of the unified model to predict mobile communication technology adoption by adding a path from effort expectancy to performance expectancy. Successively, a path was suggested from social influence to performance expectancy. The respecified model generated a good fit, $\chi^2(49) = 77.49$, $\chi^2/df = 1.58$, SRMR = .037, TLI = .987, RMSEA = .042 (CI: .023, .059), AIC = 135.49, ECVI = .41 (CI.: .35, .49). Table 7.15 summarizes the original (uncorrected) mean and standard deviation, Cronbach's α, the factor loading (β), and the squared multiple correlation (R^2) of the observed indicators to predict mobile video phone adoption.

Table 7.14

Correlation Matrix of the Observed Variables, Mobile Phone Usage, and SMS Usage

		1	2	3	4	5	6	7	8	9	10	11	12
1	PE1	-	.63	.67	.24	.13	.11	.32	.35	.37	.40	.40	.37
2	PE2		-	.75	.22	.13	.11	.49	.42	.43	.51	.51	.52
3	PE3			-	.20	.17	.15	.49	.45	.46	.57	.55	.58
4	EE1				-	.45	.54	*.09*	*.01*	*.01*	.15	.18	.13
5	EE2					-	.61	*.02*	*.01*	*.00*	*.09*	*.09*	*.08*
6	EE3						-	*.00*	*.00*	*.01*	.11	.15	.12
7	SI1							-	.61	.62	.38	.42	.42
8	SI2								-	.80	.39	.44	.43
9	SI3									-	.38	.42	.43
10	INT1										-	.88	.93
11	INT2											-	.92
12	INT3												-

Note. Correlations significant at $p < .05$, non-significant correlations are in Italic.

Path model. The path model with standardized path coefficients is featured in Figure 7.8. The standardized path coefficients in Figure 7.8 show a significant direct effect of performance expectancy and social influence on behavioral intention to adopt mobile video phone, and a non-significant direct effect of effort expectancy on behavioral intention to adopt mobile video phone. Although the direct effect of performance expectancy on mobile video phone intention is stronger than the effect of social influence; the total effect of social influence (β = .55) on mobile video phone intention surpasses the direct effect of performance expectancy on mobile video phone intention. The significant total effect of social influence on behavioral intention to adopt mobile video phone is the sum of the direct effect of social influence on behavioral intention and the indirect effect of social influence on behavioral intention to adopt mobile video phone (β = .30), mediated by the significant direct effect of social influence on performance expectancy. The significant indirect effect of effort expectancy on behavioral intention (β = .12) is mediated by the significant direct effect of effort expectancy on performance expectancy. Squared multiple correlations provide information about the variance accounted for by the complete set of variables and showed that behavioral intention was accounted for 46% (see Table 7.15).

Table 7.15

Descriptive Statistics, Factor Loadings, Squared Multiple Correlations, and Cronbach's Alpha of the Observed Indicators to Predict Mobile Video Phone Intention

	M	*SD*	β	R^2
Behavioral Intention (α = .97)				.46
I plan to use mobile video phone in the next three months	1.56	1.18	.94	.89
I predict I would use mobile video phone in the next three months	1.58	1.20	.96	.92
I intend to use mobile video phone in the next three months	1.51	1.11	.97	.93
Performance expectancy (α = .86)				.40
I would find mobile video phone useful in my daily life	2.83	1.80	.74	.55
Using mobile video phone enables me to accomplish tasks more quickly	2.36	1.64	.84	.70
I would find benefit in using mobile video phone	2.46	1.66	.90	.81
Effort expectancy (α = .77)				.00
I would find mobile phone easy to use	5.23	1.54	.65	.42
To operate mobile video phone is no problem for me	5.21	1.78	.72	.52
Learning to use mobile video phone is easy for me	5.69	1.46	.83	.69
Social influence (α = .86)				.00
People who influence my behavior think I should use mobile video phone	2.06	1.50	.70	.49
People who are important to me think that I should use mobile video phone	1.92	1.45	.88	.77
People whose opinion I value think I should use mobile video phone	1.93	1.38	.90	.80

Note. The R^2 of a latent dependent predictor is the percent of the variance in the latent dependent variable accounted for by the latent independent variable. The R^2 of an observed indicator is the estimated percent variance explained in that variable. In other words, the error variance of a variable is approximately 1 minus the percent of the variance of the variable itself.

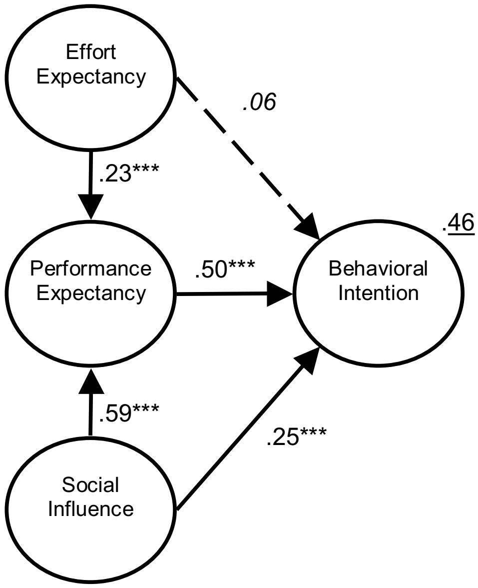

Figure 7.8. Standardized path coefficients of the unified model of acceptance and use of technology to predict mobile video phone adoption. The observed indicators of the latent construct are not shown (see Table 7.15).
Note. ***$p < .001$. Dotted lines are non-significant paths (non-significant factor loadings in Italic). Squared multiple correlations are underlined.

7.5 Model Comparison

Table 7.16 summarizes the values of the fit indices of the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology in the context of explaining mobile phone use. Table 7.17 summarizes the values of the fit indices of the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology in the context of predicting mobile video adoption.

Fit indices cutoff criteria. According to the cutoff criteria of the fit indices values proposed in chapter 6, the χ^2/df ratio should not exceed 5 for models with a good fit. The standardized root mean square residual (SRMR) which is the average difference between the predicted and observed variances and covariances in the model, based on standardized residuals should have a value less than .08 to be considered as a good fit. The Tucker-Lewis index (TLI) reflects the proportion by which the researcher's model improves fit compared to the null model (random variables) and penalizes for model complexity. A TLI value above .95 indicates a good fit, a value between .90 and .95 indicates an acceptable fit, and a value below .90 indicates a need to respecify the model. The root mean square error of approximation (RMSEA) which reflects the discrepancy per degree of freedom, corrects for model complexity and is less affected by sample size should be less than or equal to .05. A value less than or equal to .08 indicates an adequate fit, and a value greater than .10 indicates a poor fit.

Table 7.16

Fit Indices Values of the Three Models to Explain Mobile Phone Use

	Model of Media Attendance	Expectancy-Value Judgments Model of Uses & Gratifications	Unified Model of Acceptance and Use of Technology
N	334	310	320
Variables[a]	67	59	38
χ^2	521.89	416.17	163.63
DF	236	180	72
χ^2/df	2.21	2.31	2.27
SRMR	.102	.076	.071
TLI	.936	.937	.953
RMSEA	.060 (CI: .053, .067)	.065 (CI: .057, .073)	.063 (CI: .050, .076)
AIC	649.89	518.17	229.63
ECVI	1.95 (CI: 1.77, 2.16)	1.68 (CI: 1.50, 1.88)	.72 (CI: .62, .85)
R^2	.76	.69	.48

Note. [a]The number of variables in the evaluated model of media attendance is less than in the hypothesized model because of the exclusion of the expected outcomes status and novelty. Also the number of variables in the evaluated unified model of acceptance and use of technology is less than in the hypothesized model because of the exclusion of facilitating conditions. These exclusions might have had influence on the values of the fit indices and on the percentage explained variance of mobile phone use accounted for by both models.

The fit indices values in Table 7.16 and 7.17 show that all three models in the context of mobile phone use as well as in the context of mobile video phone met the χ^2/df ratio criterion. Also the SRMR values of all three models show a good fit, except for the model of media attendance to explain mobile phone use. The TLI of the three models in the context to explain mobile phone use indicate an acceptable fit, except for the unified model of acceptance and use of technology, which is a good fit. In the context of predicting mobile video phone, the TLI of the three models indicate a good fit, except for the expectancy-value judgments model of uses and gratifications, which indicates an acceptable fit. The RMSEA values of all three models are adequate, except for the unified model of acceptance and use of technology in the context of mobile video phone adoption, which show a good fit.

Table 7.17
Fit Indices Values of the Three Models to Predict Mobile Video Phone Adoption

	Model of Media Attendance	Expectancy-Value Judgments Model of Uses & Gratifications	Unified Model of Acceptance and Use of Technology
N	310	320	334
Variables	77	55	32
χ^2	834.00	419.72	77.49
DF	337	163	49
χ^2/df	2.48	2.58	1.58
SRMR	.040	.086	.037
TLI	.948	.943	.987
RMSEA	.069 (CI: .063, .075)	.070 (CI: .062, .079)	.042 (CI: .023, .059)
AIC	972.00	513.72	135.49
ECVI	3.15 (CI: 2.88, 3.43)	1.61 (CI: 1.43, 1.81)	.41 (CI: .35, .49)
R^2	.41	.22	.46

Alternative model comparison measures. To compare the three structural equation models to determine which model is preferred against the two alternative models, the Akaike information criterion (AIC) and the expected cross-validation index (ECVI) are used (see chapter 6). Both AIC and ECVI are used to compare (non-nested) models and are not interpreted for a single model. AIC reflects the discrepancy between model-implied and observed covariance matrices, and adjusts model chi-square to penalize for model complexity. The absolute value of AIC has no intuitive value, except by comparison with another AIC, in which case the lower AIC reflects the better-fitting model. ECVI, like AIC reflects the discrepancy between model-implied and observed covariance matrices, but penalizes for model complexity more than AIC. Lower ECVI indicates a better fit.

The values of the AIC and ECVI show that in the context of mobile phone use (see Table 7.16) and in the context of mobile video phone adoption (see Table 7.17), the unified model of acceptance and use of technology has lower values of AIC and ECVI compared to the expectancy-value judgments model of uses and gratifications, and the model of media attendance.

7.6 Summary of the Results

In this chapter the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology were evaluated and compared in the context of mobile phone use as well as in the context of mobile video phone adoption. The summarized findings are described below and will be discussed in more detail in chapter 10.

Model evaluation and comparison. The values of the fit indices show that all three models have an adequate fit in the context of mobile phone use and mobile video adoption, with the exception of the unified model of acceptance and use of technology, which has a good model fit in both contexts. The empirical comparison of the three models shows that the unified model of acceptance and use of technology surpasses the two alternative models.

Mobile phone use. According to the expectancy-value model of uses and gratifications, the strongest predictors to explain mobile phone usage are intention and expectancy-value judgments, with mobility as strongest contributor to expectancy-value judgments. According to the model of media attendance, the strongest predictor to explain mobile phone usage is habit strength. Behavioral intention is the sole predictor of the unified model of acceptance and use of technology to explain mobile phone usage, with performance expectancy as the strongest predictor of behavioral intention. The other predictor expected to have an effect on mobile phone use (i.e., facilitating conditions) was not internally consistent, and was therefore excluded from further analyses. The percentage explained variance of mobile phone use accounted for by the expectancy-value model of uses and gratifications was 69%, the percentage explained variance accounted for by the model of media attendance was 76%, and the percentage explained variance accounted for by the unified model of acceptance and use of technology was 48%. The exclusion of facilitating conditions might have had influence on the percentage explained variance of mobile phone use accounted for by the unified model of acceptance and use of technology.

Mobile video phone adoption. According to the expectancy-value model of uses and gratifications, the strongest predictor to explain mobile phone adoption is expectancy-value judgments. The strongest contributors to expectancy-value judgments are relaxation and novelty. According to the model of media attendance, the strongest predictor of mobile video phone adoption is expected outcomes, with activity, status, and monetary outcomes as strongest contributors of expected outcomes. Social influence is the strongest predictor to explain mobile video adoption according to the unified model of acceptance and use of technology. The percentage explained variance of mobile video phone adoption accounted for by the expectancy-value model of uses and gratifications was 22%, the percentage explained variance accounted for by the model of media attendance was 41%, and the percentage explained variance accounted for by the unified model of acceptance and use of technology was 46%.

Expectancy-value judgments. With regard to the expectancy-value judgments model of uses and gratifications the results indicate that both in the context of mobile phone use and mobile video phone adoption, expectancy-value judgments have a stronger effect on attitude towards intention to use a mobile phone or to adopt mobile video phone, than on mobile phone or mobile video phone intention and mobile phone usage.

Model of media attendance. The results of testing the model of media attendance in the context of mobile phone use show that habit strength is a stronger predictor of mobile phone usage than expected outcomes. While in the context of mobile video phone adoption the opposite is true. This finding could imply a reciprocal relationship between habit strength and expected outcomes.

Social influence. In contrast to the absence of perceived normative expectations in determining people's behavioral intention to use a mobile phone, it appeared that perceived normative expectations played a role in determining people's intentions to adopt mobile video phone in both the model of expectancy-value judgments and the unified model of acceptance and use of technology.

Interpreting the empirical findings of the three structural equation models are but one piece of information using in comparing and evaluating the three alternative models to explain and predict mobile communication technology behavior. Other information that also will be considered includes factors such as theoretical scope, theoretical interpretability, and faithfulness of the three alternative models (see chapter 5). In the next chapter, a theoretical evaluation and comparison of the three models will be presented.

8

Theoretical Comparison of Three Models to Explain and Predict Mobile Communication Technology Behavior

In the previous chapter the expectancy-value judgments model of uses and gratifications, the model of media attendance, and the unified model of acceptance and use of technology were empirically evaluated and compared on the basis of quantitative criteria. In this chapter a theoretical evaluation and comparison of the three models will be presented based on the qualitative criteria as proposed in chapter 5.

8.1 Preliminary Theoretical Comparison

The provisional comparison of the three models to explain and predict mobile communication technology behavior in Chapter 4 indicated that all three models are concerned with the understanding of the same phenomenon of interest, i.e., media technology acceptance and use. However, the expectancy-value judgments model of uses and gratifications is more than the other two models concerned with people's attitude and beliefs towards media use, while the model of media attendance is more concerned about behavioral mechanisms such as outcome expectations, habit strength, and self-regulation that influence people's media use. The unified model of acceptance and use of technology is more than the other two models concerned with people's beliefs toward required effort and gains in performance associated with the use of a particular media technology in an organizational context.

Also, the preliminary theoretical comparison of the three models in Chapter 3 indicated that the three models converge on central processes and phenomena, and demonstrated that some of the constructs of the three models (e.g., self-efficacy and facilitating conditions, attitude and outcome expectations) address the same phenomenon but are labeled differently (cf. 'jingle fallacy'; Marsh, 1994). To more systematically evaluate and compare the three media use models, the models will be evaluated and compared against the qualitative criteria as described in Chapter 5.

As already stated in Chapter 4, all three models comply with the essential criteria necessary to be recognized as generally accepted models in the practice of science. The three models are falsifiable as several studies have supported the models and its assumptions, which might indicate that the assumptions of all three models are plausible and consistent with established findings. Since prior research studies (see Chapter 3) have already established that all three models are logically consistent, consistent with accepted facts, and testable, one might therefore consider all three models to have met the necessary criteria as a matter of fact. Consequently, as proposed in chapter 5, only the following qualitative criteria will be used to theoretically evaluate and compare the three models: (a) theoretical scope (or generality); (b) theoretical interpretability; (c) faithfulness; and (d) parsimony (or logical simplicity).

8.2 Theoretical Scope

Theoretical scope or generality refers to the degree to which a model can be extended to include situations and events not specifically included in the phenomena that the model is supposed to explain (Myung, Pitt, & Kim, 2005).

Originating from general social psychological theories about human behavior, the core features of both the expectancy-value judgments model of uses and gratifications and the model of media attendance are in itself general concepts that describe and explain general mechanisms in human behavior. Examples of such general concepts are for instance attitude and subjective norm in the expectancy-value judgments model of uses and gratifications, or habit strength, self-efficacy and self-regulation in the model of media attendance. Because these theoretical concepts are expected to be applicable to general human behavior, the same concepts are then also likely to be applicable to specific human behaviors such as media technology behavior.

Although most of the eight models from which the unified model of acceptance and use of technology was synthesized also stem for the same background theories as the other two models, the original scope of the unified model is to explain individual-level technology-adoption (Venkatesh, 2006) in an organizational context, such as people's workplace; for example, the predecessor of the unified model – the technology acceptance model (Davis et al., 1989) – was initially concerned with the acceptance of computer software. Venkatesh (2006) posed that one of the greatest strengths of models, such as the technology acceptance model, has been their generalizability across a wide range of technologies and settings over several years. According to Stafford et al. (2004), the unified model of acceptance and use of technology generally is a study of technology usage choices in the workplace – a scenario where technology adoption has already occurred through organizational selection and procurement processes – and the goal of such research is usually to determine whether and how employees will choose to make use of the innovation already present in the organization. Social influence in the unified model generally appears in the form of normative forces that serve extrinsic purposes related to compliance with organizational goals (Stafford et al., 2004).

It is not so much that the unified model of acceptance and use of technology incorporates general mechanisms of human behavior derived from general theories of human behavior, which are responsible for the generalizability of the model. It is more because two specific concepts of the unified model, (i.e., performance expectancies, and effort expectancies) are so generally applicable and appealing to explain all kinds of human behavior not necessarily limited to the context of acceptance and use of technology, that these concepts are widely applied to explain all kinds of human behavior; for example, in terms of reach, technology acceptance models have been applied in a variety of domains, from marketing contexts to green electricity use to dairy farming (Venkatesh, 2006).

The danger is, however, that the unified model of acceptance and use of technology when extended beyond its original context, and because of its alluring and simple proposition, becomes so general in explaining human behavior that the determinants of a specific human behavior are reduced to these broad concepts such as performance and effort expectancies regardless of the context of the behavior in question. According to Venkatesh (2006), the types of constructs employed in individual-level technology-adoption research have primarily been technology-centric perceptions. While there has been a call for richer theorizing by giving deeper consideration to various aspects of the technology and the context, little research has actually been done at the individual level (p. 498).

In general (cf. Shaw & Constanzo, 1970), the more comprehensive, the less restrictive, and the more general a model, the more valuable a model is likely to be. In terms of generalizability, the scope of both the expectancy-value judgments model of uses and gratifications and the model of media attendance can be extended to include situations and events not specifically included in the phenomena that the model is supposed to explain because the theoretical concepts used in the two models stem from general social psychological theories about human behavior. That is, the general theoretical scope of the underlying social psychological theories has been used to explain and predict a specific human behavior, i.e., media technology behavior.

In contrast to the other two models, the specific quality of the constructs of the unified model of acceptance and use of technology to explain and predict individual-level technology-adoption in an organizational context may limit the theoretical generalizabilty of the unified model. The constructs of the unified model are specifically operationalized to be employed in an organizational context. Although the unified model has been extended well beyond its initial scope and it has been applied in a variety of domains, this does not automatically guarantee that the generalizability of the theoretical scope of the unified model can be extended to theoretically explain situations and events not specifically included in the phenomena that the unified model is supposed to explain. That is, employing the specific constructs of the unified model to explain and predict general media behavior might not be theoretically justifiable.

8.3 Theoretical Interpretability and Faithfulness

Because the two qualitative criteria theoretical interpretability and faithfulness are strongly related, both criteria will be used to evaluate and compare the three models simultaneously. According to Myung, Pitt, and Kim (2005), a model must be interpretable in the sense that a model makes sense and is understandable. Most importantly, the components of the model must be linked to theoretical constructs. A model is said to be faithful to the extent that the model's ability to capture the underlying phenomenon of interest originates from the theoretical principles embodied in the model, rather than from the choices made in its computational instantiation (Myung, Pitt, & Kim, 2005).

Expectancy-value judgments model of uses and gratifications. The constructs of the expectancy-value judgments model of uses and gratifications (i.e., behavioral intention, subjective norm, and attitude) are all linked to the theoretical constructs of the theory of reasoned action (Fishbein & Ajzen, 1975), with the exception of the expectancy-value judgments. The expectancy-value judgments are derived from prior uses and gratifications studies. The most common method within the uses and gratifications tradition to cluster people's gratifications is to transform an extensive list of potential gratifications sought into several gratification dimensions (factors) by means of an exploratory factor analysis (see Peters & Ben Allouch, 2005). The consequence of statistically constructed gratification clusters is that each uses and gratifications study proposes its own list of gratifications. Even when the same labels are used (e.g., convenience, fashion, entertainment) to cluster the gratification items, a situation can occur where in two different studies a particular gratifications scale is labeled differently but is actually measuring the same construct (jingle fallacy; Marsh, 1994), or that two particular gratifications scales are addressed with the same label, but measure different constructs (jangle fallacy). As the expectancy-value judgments are derived from empirical uses and gratifications studies rather than theoretically constructed, the expectancy-value model of uses and gratifications is less faithful to the extent that the model's ability to capture the underlying phenomenon of interest to a lesser extent originates from the theoretical principles embodied in the model.

Unified model of acceptance and use of technology. Because the unified model of acceptance and use of technology is synthesized out of eight previously established models (Venkatesh et al., 2003), the background theories of these eight models indirectly constitute the underlying theoretical principles of the unified model. However, according to Venkatesh et al. the unified model of acceptance and use of technology captured only the essential elements of the eight models. For practical analytical reasons, Venkatesh et al. operationalized each of the core constructs in the unified model by using the highest-loading items from each of the respective scales; for example, the scale that measures performance expectancy is constructed out of four items that come from three different constructs, i.e., perceived usefulness, relative advantage, and outcome expectations. These three different constructs also stem from three different theoretical perspectives, i.e., technology acceptance model, diffusion of innovation theory, and social cognitive theory (Venkatesh et al., p. 447). Picking the highest-loading items out of several different scales that measure different constructs, which also belong to different theoretical perspectives, results in an eclectic model that is constructed on the basis of computational instantiation, rather than on the basis of choices that originate from theoretical principles. Moreover, following Bandura (1997, p. 11), it can be argued that combining diverse attributes into a single index creates confusion about what is actually being measured and how much weight is given to particular attributes in the forced summary judgment.

Model of media attendance. Compared to the other two models, the model of media attendance is probably the model that is most in accordance with and faithful to its background theory from which it is derived; for example, outcome expectations in the model of media attendance are organized around six basic types of incentives for human behavior. These types of incentives are theoretically constructed on the basis of social cognitive theory (Bandura, 1986), rather then statistically derived from exploratory factor analysis (LaRose & Eastin, 2004) as is the case with expectancy-value judgments. The same is true for the other components of the model of media attendance (e.g., self-efficacy, habit strength, deficient self-regulation). The interpretability of the underlying theoretical mechanisms that are embodied in the model of media attendance to explain media behavior differs from the unified theory of acceptance and use of technology and in a lesser extent to the expectancy-value judgments model of uses and gratifications. More than in the two other models, the model of media attendance explicitly describes the dynamics between the various components in the model on the basis of its underlying background theory (see paragraph 4.3).

The unified theory of acceptance and use of technology does not explicitly describe how changes between the dynamics of the key concepts of the model influence media behavior; for example, how should one interpret a situation where effort expectancy is the most important determinant in explaining a particular use of media technology and the effect of for instance performance expectancy equals to zero? There is (yet) no underlying theoretical principle that might help to interpret the dynamics between the components of the unified model of acceptance and use of technology. To a lesser extent, the expectancy-value judgments model of uses and gratifications also lacks an underlying theoretical explanation to interpret some of the dynamics between components of the model. The expectancy-value judgments model of uses and gratifications does not explain for example, why expectancy-value judgments have a stronger influence on attitude than on intention.

8.4 Parsimony and Adequacy of Theoretical Explication

Parsimony or logical simplicity refers to the notion that a model should explain phenomena with as few variables as possible. However this should not mean economy at the expense of adequacy of theoretical explication (cf. Shaw & Constanzo, 1970). A model should also provide an adequate explanation for the phenomenon of interest supported by substantial theoretical arguments (see paragraph 5.1.2). One should be careful with parsimony, as highly parsimonious models may be overly simple and may leave out many important variables that expand insight into what is happening (cf. Littlejohn & Foss, 2005). Therefore, the parsimony of all three models will be compared in relation to its adequacy of theoretical explication.

In terms of number of variables, the model of media attendance is more complex compared to the other two models, and therefore less parsimonious. However, in terms of explaining the underlying regularities and mechanisms in media behavior (i.e., adequacy of theoretical explication), the model of media attendance is more descriptively adequate than the unified model of acceptance and use of technology, and to a lesser extent more descriptively adequate than the expectancy-value model of uses and gratifications.

It is not so much that the model of media attendance is more descriptively adequate because the model counts more variables, but that the variables in the model represent interrelated theoretical mechanisms and that the exogenous variables also are included in the model. Variables which are thought to be independent of other variables in a model are termed exogenous variables; for example, when habit strength in the model of media attendance is found to be the strongest determinant in the usage of a particular media technology, an inspection of the values of the causally prior variables of habit strength (i.e., the exogenous variables) and the underlying interrelated mechanism of habit strength, self-efficacy, and expected outcomes might indicate that this strong effect of habit strength in using this particular media technology is caused by achieving satisfactory outcomes. Further, it might indicate that self-efficacy as the progressive mastery of the media behavior concerned does not influence expected outcomes because habitualized users do not longer have to learn how to obtain successful outcomes.

In contrast, when for example effort expectancy in the unified model of acceptance and use of technology is found to be the strongest determinant in using a particular media technology, the unified model does not explain what might have caused this strong influence. This means that effort expectancy is an endogenous variable in the unified model – that is, subject to the influence of causally prior variables. However, no causally prior variables are included in the model to further explain this effect, other than a potential mediating effect of the key moderators gender, age, and experience.

The reason why the model of media attendance is to a lesser extent more descriptively adequate than the expectancy-value judgments model of uses and gratifications, is that the causally prior variables in the model, i.e., expectancy-value judgments are in contrast to the variables in the model of media attendance, statistically derived, rather than theoretically constructed, as it was explained above.

8.5 Summary of the results

In general, models function as visual aids which help to better understand, interpret, and evaluate the relationships among the various parts of the phenomenon of interest (see Chapter 4). Theory-driven models also indicate not only what to observe but how to observe, as well as they enable the researcher to make predictions about outcomes and effects in the observed data. Because models are, by definition, constructions and therefore leave out a lot, they are in a sense, all false, incomplete, and inadequate (Levins, 1966) to fully grasp the complexity of people's media technology behavior, and greatly oversimplify in its attempt to explain basically complex social behavior.

However, on the basis of the comparison in this chapter between the three models against the qualitative criteria, the model of media attendance is expected to be the most appropriate theory-driven model to make predictions about outcomes and effects of media technology behavior because it is the most elaborated model in terms of expressing underlying causal mechanisms that are of influence on media technology behavior.

In the next chapter, conclusions will be drawn from both the results of the empirical and theoretical comparison of the three models to explain and predict mobile communication technology behavior in an attempt to answer the two key research questions presented in Chapter 1. Finally in Chapter 10, the conclusions that are drawn from the empirical and theoretical comparison of three models and their implications will be discussed.

9

Conclusions

In this dissertation three media use models and their extensions are discussed and both empirically and theoretically compared within the context of mobile communication technology use. In this chapter conclusions will be drawn from the findings of both the empirical and theoretical comparison. In the next chapter the conclusions presented in this chapter and their implications will be discussed in more detail.

9.1 Empirical Comparison

The first key research question to be answered in this dissertation is concerned with the empirical power of the three models to explain and predict mobile communication technology behavior. In Chapter 1, the first key research question was stated as follow:

> *RQ1: Which current media use model statistically best explains the use and predicts the adoption of mobile communication technology?*

The empirical comparison of the three models presented in Chapter 7 shows that in terms of alternative model comparison measures (i.e., the Akaike information criterion, and the expected cross-validation index) and based on the values of the model fit indices, the unified model of acceptance and use of technology surpasses both the model of media attendance and the expectancy-value judgments model of uses and gratifications in both the context of mobile phone use and mobile video phone adoption.

However, the empirical findings in Chapter 7 also show that only the initial measurement and structural model of the expectancy-value judgments model of uses and gratifications did fit the data well in both the context of explaining mobile phone use and predicting mobile video phone adoption.

In the context of explaining mobile phone use, the measurement model of the model of media attendance had to be modified to improve model fit by excluding two outcome expectancies (i.e., status, and novelty). Also, in the context of explaining mobile phone use, the initial structural model did not fit the data well. The structural model was improved by correlating the error terms of habit strength with monetary outcomes, and self-reactive outcomes with both activity outcomes and deficient self-regulation. In the context of predicting mobile video phone, both the measurement and structural model showed a good fit.

The measurement model of the unified model of acceptance and use of technology in the context of explaining mobile phone use had to be modified because the internal consistency of the measure facilitating conditions was below aspiration level. Also, the structural model had to be respecified because the initial structural model did not fit the data. A path from effort expectancy to performance expectancy was added to improve model fit. Also, in the context of predicting mobile video phone, the structural model of the unified model of acceptance and use of technology was modified to improve model fit by adding a path from effort expectancy to performance expectancy, and a path from social influence to performance expectancy.

In sum, these finding indicate that in the context of explaining mobile phone use both the initial model of media attendance and the initial unified model of acceptance and use of technology had to be modified to fit the data. In the context of predicting mobile video phone adoption the initial unified model of acceptance and use of technology had to be modified to fit the data.

A comparison of the three models in terms of explained variance, that is, the variance accounted for by the complete set of variables of each model, is only possible in the context of predicting mobile video phone adoption. Because of the exclusion of the expected outcomes status and novelty in the model of media attendance, and the exclusion of facilitating conditions in the unified model of acceptance and use of technology, a fair comparison between the three models in the context of explaining mobile phone use is not possible. The exclusions might have had influences on the percentage explained variance of mobile phone use accounted for by both models.

The percentage explained variance in behavioral intention to adopt mobile video telephony by the unified model of acceptance and use of technology surpasses both the percentage explained variance in behavioral intention to adopt mobile video telephony by the model of media attendance and the expectancy-value judgments model of uses and gratifications.

9.2 Theoretical Comparison

The second key research question to be answered in this dissertation is concerned with the theoretical power of the three models to explain and predict mobile communication technology behavior. In Chapter 1, the second key research question was stated as follow:

> *RQ2: Which current media use model best substantially explains the use and predicts the adoption of mobile communication technology?*

As already stated in Chapter 4, all three models comply with the essential criteria necessary to be recognized as generally accepted models in the practice of science. The three models are falsifiable as several studies have supported the models and its assumptions, which might indicate that the assumptions of all three models are plausible and consistent with established findings. Since prior research studies (see Chapter 3) have already established that all three models are logically consistent, consistent with accepted facts, and testable, one might therefore consider all three models to have met the necessary criteria as a matter of fact.

The provisional comparison of the three models to explain and predict mobile communication technology behavior in Chapter 4 indicated that all three models are concerned with the understanding of the same phenomenon of interest, i.e., media technology acceptance and use. However, the expectancy-value judgments model of uses and gratifications is more than the other two models concerned with people's attitude and beliefs towards media use, while the model of media attendance is more concerned about behavioral mechanisms such as outcome expectations, habit strength, and self-regulation that influence people's media use. The unified model of acceptance and use of technology is more than the other two models concerned with people's beliefs toward required effort and gains in performance associated with the use of a particular media technology.

On the basis of the comparison between the three models with the qualitative criteria presented in Chapter 8, the model of media attendance is expected to be the most appropriate theory-driven model to make predictions about outcomes and effects of mobile media technology behavior because it is the most elaborated model in terms of expressing underlying causal mechanisms that are of influence on media technology behavior.

In conclusion, based on the findings of the empirical comparison the unified model of acceptance and use of technology should be preferred to the two alternative models. Based on the findings of the theoretical comparison the model of media attendance should be preferred to the two alternative models. The implications of this conclusion will be discussed in more detail in the next chapter. In the remainder of this chapter conclusions will be presented which can be drawn upon the empirical and theoretical findings from each media use model separately with regard to mobile communication technology behavior.

9.3 Mobile Communication Technology Behavior

Expectancy-value judgments model of uses and gratifications. Based on the empirical findings presented in paragraph 7.2 the conclusion can be drawn that the expectancy-value judgments model of uses and gratifications is capable to explain mobile phone usage to a high degree in terms of explained variance, but the model is to a lesser extent successful to predict the behavioral intention to adopt mobile video telephony. Apparently, in the context of technology adoption other mechanisms or forces not included in the expectancy-value judgments model of uses and gratifications drive people to whether or not adopt a new media technology or service.

Furthermore, in both the context of mobile phone use and mobile video phone adoption the findings show that expectancy-value judgments have a stronger influence on attitude towards intention to use a mobile phone or to adopt mobile video phone, than on mobile phone and mobile video phone intention, and mobile phone usage. This finding underlines the notion that the expectancy-value judgments model of uses and gratifications stemming from the theory of reasoned action is mainly concerned with internal processes of human behavior, such as beliefs and attitudes.

Attitudes (i.e., relatively stable ideas about whether something is good or bad) exert powerful influences on people's evaluations – their current appraisals – and these, in turn, influence people's choices (Cunningham & Zelazo, 2006). Cunningham and Zelazo posed that the terms attitude and evaluation refer to different aspects of evaluative processing: whereas an attitude is a relatively stable set of representations of a stimulus, an evaluation reflects one's current appraisal of the stimulus, including whether it should be approached or avoided. When rendering an evaluation, one draws upon pre-existing attitudes, together with novel information about the stimulus, contextual information and current goal states (p. 97).

With regard to predicting the intention to adopt a new communication technology people have not experienced yet (e.g., mobile video telephony) one can not draw upon pre-existing attitudes towards this new technology. The findings in paragraph 7.2.3 show that attitude was not a significant predictor of behavioral intention to use mobile video telephony. Apparently, assuming that one is familiar with the features of the new technology (e.g., have seen it on TV or having read about it in a magazine), a person's positive or negative feelings about using a new technology or service are less of an influence on behavioral intention than people's expectancies and the influence of significant others (see Figure 7.4).

In conclusion, the expectancy-value judgments model of uses and gratifications is primarily useful in the context to explain existing mobile communication technology behavior in terms of attitude and beliefs. However, as the expectancy-value judgments are derived from empirical uses and gratifications studies rather than theoretically constructed, the expectancy-value model of uses and gratifications is less faithful to the extent that the model's ability to capture the underlying phenomenon of interest to a lesser extent originates from the theoretical principles embodied in the model (see paragraph 8.3).

Unified model of acceptance and use of technology. The empirical findings presented in paragraph 7.4 show that within the unified model of acceptance and use of technology performance expectancy is the strongest predictor of behavioral intention in both explaining mobile phone use and predicting mobile video phone adoption. The only conclusion that can be drawn from this finding is that people's intention to use or adopt a particular mobile communication technology is influenced by the expectation that this particular mobile communication technology is useful in their daily lives, enables to accomplish tasks more quickly, or is beneficial (see paragraph 7.4.2). As already stated in paragraph 8.4, the unified model of acceptance and use of technology does not explain what might have caused this strong influence of performance expectancy on behavioral intention because no causally prior variables are included in the unified model to further explain the effect of performance expectancy.

Another conclusion that can be drawn concerns the influence of perceived normative expectations or social influence. Like in the expectancy-value judgments model of uses and gratifications (see paragraphs 7.2.2 and 7.2.3), the empirical findings presented in paragraphs 7.4.2 and 7.4.3 show that within the unified model of acceptance and use of technology social influence is a significant predictor of behavioral intention to adopt mobile video telephony, and is not a significant predictor of behavioral intention to use a mobile phone. Apparently, perceived normative expectations play only a role in determining people's intentions to adopt new mobile communication technology; that is technology that is not already accepted.

Furthermore, the findings show that within the unified model of acceptance and use of technology effort expectancy is not a significant predictor of behavioral intention to use a mobile phone or to adopt mobile video telephony. Apparently, in the context of mobile communication technology behavior effort expectancy has no direct influence on behavioral intention.

To improve the fit of the unified model of acceptance and use of technology, a path from effort expectancy to performance expectancy had to be added in both the context to explain mobile phone use and to predict mobile video phone adoption. Although in the original unified model (Venkatesh et al., 2003) both effort and performance expectancy are hypothesized as two independent constructs, previous empirical studies (see Bouwman, Van den Hooff, Van de Wijngaert, & Van Dijk, 2005) on the predecessor of the unified model, the technology acceptance model (Davis et al., 1989) often have found that perceived ease of use (similar to effort expectancy) is a determinant of perceived usefulness (similar to performance expectancy). Figures 7.7 and 7.8 show that within the unified model of acceptance and use of technology, the indirect effect of effort expectancy is mediated via a direct effect on performance expectancy. This might lead to the conclusion that the influence of effort expectancy (i.e., whether or not a particular mobile communication technology is easy to use or easy to learn) on people's behavioral intention is fully incorporated by the influence of performance expectancy.

In the context of predicting mobile video phone adoption also a path from social influence to performance expectancy had to be added to improve model fit (see Figure 7.8). In retrospect, this addition to the unified model makes sense as it is plausible that the influence of significant others might also be of influence on people's expectations about the performance of mobile video telephony; for example, 'I would find mobile video useful in my daily life' (performance expectancy) because 'people who are important to me think I should use mobile video phone' (social influence). However, this connection between social influence and performance expectancy is not in accordance with the unified theory of acceptance and use of technology (Venkatesh et al., 2003). Nevertheless, without the addition of the path from social influence to performance expectancy the unified model to predict mobile video phone adoption would not fit the data.

A final conclusion that can be drawn concerns the measure facilitating conditions. The internal consistency of the measure facilitating conditions in the context to explain mobile phone use was below aspiration level in both the pre-test and the sample. Venkatesh et al. (2003) have defined facilitating conditions as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system (p. 453). The use of mobile communication technology is however a more general media behavior not necessarily applied within an organizational context. With regard to explaining general media behavior, the definition of facilitating conditions is too specifically formulated. As already stated in paragraph 3.4 conceptually, perceived behavioral control, facilitating conditions, and self-efficacy are very similar concepts. It is not too say that the very specific definition of facilitating conditions is the reason why the measure was below aspiration level in the context to explain mobile communication technology use. However, when the unified model of acceptance and use of technology is applied to explain general media behavior beyond an organizational context, facilitating conditions might be replaced with either perceived behavioral control as defined by Ajzen (1991) or self-efficacy as defined by Bandura (1997).

In conclusion, the specific quality of the constructs of the unified model of acceptance and use of technology may limit the generalizabilty of the unified model beyond its organizational context. Employing the specific constructs of the unified model to explain and predict general media behavior might not be theoretically justifiable. In the context of mobile communication technology behavior adjustments had to be made to the original unified model to improve model fit, however these post hoc alterations – although plausible – are based on computational instantiation, rather than on the basis of choices that originate from theoretical principles. Furthermore, no causally prior variables are included in the unified model to further explain the dynamics between the different constructs of the unified model of acceptance and use of technology.

Model of Media Attendance. The empirical findings (see paragraph 7.3) of testing the model of media attendance in the context of mobile phone use show that habit strength is a stronger predictor of mobile phone usage than expected outcomes. While in the context of mobile video phone adoption the opposite is true. As already stated in paragraph 7.6, this finding could imply a reciprocal relationship between habit strength and expected outcomes.

The empirical results also show a strong effect of expected outcomes on prospective habit strength with regard to predicting mobile video telephony (see Figure 7.6). This result supports the notion that as long as media use is not fully habitualized, habit strength is causally determined by outcome expectations, which precede habit strength in time (LaRose & Eastin, 2004).

On the basis of the mediating effect of habit strength on the influence of expected outcomes on mobile phone usage (see Figure 7.5) one might conclude that the relationship between expected outcomes and habit strength depends on the stage of individual habitualization. This conclusion makes sense, as in the Netherlands the stage of the habitualization process of the mobile phone is almost complete (see paragraph 7.1). Once mobile communication technology behavior is more strongly determined by habit strength, the effect of outcome expectations may no longer have much influence on people's mobile communication technology behavior, because people are no longer aware of the relative importance of expected outcomes or no longer have expectations because the outcomes are already known.

The results of testing the model of media attendance support the findings of Peters and Ben Allouch (2005) that people are initially influenced more strongly by perceptions about the expected use, but over time, due to the quick habituation of new media technology, initial expectations become latent.

Apparently, initial expectations are reflections of a relatively short moment in time, subjected to changes over time. Once outcome expectations become habitual it becomes difficult to explain media behavior solely by expected outcomes. Aarts et al. (1998) posed that when behavior is performed repeatedly and becomes habitual, it is guided by automated processes, rather than being precede by elaborate decision processes. Therefore the relative importance of expected outcomes as stated by LaRose and Eastin (2004, p. 371) to predict media consumption to an unprecedented degree is only supported when habit strength is not already very pronounced.

This conclusion is also reflected in the path from mobile phone experience via self-efficacy to habit strength with regard to explaining mobile phone use (see Figure 7.5). Whereas with regard to predicting mobile video adoption, the path from mobile phone experience via self-efficacy goes to expected outcomes (see Figure 7.6). This might lead to the conclusion that with regard to mobile video phone adoption, where users still need to learn how to successfully obtain expected outcomes, self-efficacy as the progressive mastery of the media behavior in question (LaRose & Eastin, 2004) increases with experience. LaRose and Eastin (2004) posed that once users achieve satisfactory means for attaining those outcomes, they should become increasingly inattentive to specific behaviors that support them. In the case where mobile communication technology use is almost habitualized, self-efficacy does not influence expected outcomes anymore as habitualized users do not longer have to learn how to obtain successful outcomes.

In conclusion, the empirical findings of testing the model of media attendance support the assumption that within the model of media attendance mobile communication technology use is more likely to be explained by habit strength and mobile communication technology adoption is more likely to be predicted by outcome expectations. Furthermore, the variables in the model represent interrelated theoretical mechanisms. Also, the model of media attendance explicitly describes the dynamics between the various components in the model on the basis of its underlying background theory (see paragraph 4.3) and has also included explanatory exogenous variables.

10

Discussion

In this final chapter the conclusions drawn from the findings of both the empirical and theoretical comparison of the three media use models presented in the previous chapter and their implications will be discussed in more detail. Subsequently, the limitations of the study will be acknowledged, followed by implications for using models in media use research.

10.1 General Discussion of the Findings

This dissertation focused on the social psychological determinants of mobile communication technology use and adoption in an attempt to better understand people's behavior for adopting and using innovative information and communication technologies. In particular, this study emphasized the comparison of three media use models to explain and predict media technology behavior from different theoretical perspectives.

An examination of the background theories from which the three media use models originate indicated that there are several theoretical connections and similarities between the three theoretical perspectives with regard to the central processes and phenomena of interest. Yet, all three models propose different determinants to explain and predict media technology behavior.

Briefly stated, from a uses and gratifications research perspective, media technology behavior is determined by needs that generate expectations of the media technology, which lead to differential patterns of media technology exposure, resulting in need gratifications and other consequences (Katz, Blumler, & Gurevitch, 1974). Media technology behavior from an expectancy-value perspective that has been incorporated into uses and gratifications research is determined by the behavioral intention to use media technology. Behavioral intention, is in turn, a function of attitude towards the behavior (the sum of the perceived values of the need-driven expectations of the media technology), subjective norms, and in case the attainment of behavioral goals is not under volitional control, perceived behavioral control (cf. Ajzen, 1991; Fishbein & Ajzen, 1975). From a social cognitive perspective, media technology behavior is determined by exercising forethought (e.g., outcome expectations), reflecting on one's own behavior (e.g., self-efficacy), applying self-reactive motivating influences (e.g., self-regulation, habit), and the interaction with the environment (cf. Bandura, 2001). Within the unified theory of acceptance and use of technology, media technology behavior is determined by performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al, 2003).

As the results of this study indicated, it makes quite a difference which determinants are most important to explain media technology behavior because the explanatory significance of a particular determinant all depends on the stage of development and diffusion the media technology is in (e.g., a well-accepted media technology such as the mobile phone versus a new innovative media technology such as mobile video phone). The findings of this study indicate that each of the three models has its own quality in explaining mobile communication technology behavior. As all three models are recognized as generally accepted models in the practice of science and appropriate for the explanation and prediction of media technology behavior, the aim of this study was not to evaluate and compare the three alternative models in terms of good or bad, weak or strong. Instead, the models are evaluated on a continuum that range from 'very useful at one end' to 'not particular useful at the other end' (cf. Daiton & Zelley, 2005) to either predict or explain mobile communication technology behavior. The findings of this study indicate that each model has its own unique contribution in either the explanation or prediction of media technology behavior.

Expectancy-value judgments model of uses and gratifications. The expectancy-value judgments model of uses and gratifications is most useful to explain media behavior in terms of expectations and beliefs as it describes what kind of gratifications people seek (reformulated as expectancy-value judgments) in using a particular media technology. However, for each new media technology that is introduced one needs to establish first and foremost the expectancy-value judgments clusters that match the use of this particular new media technology. Therefore, the strength of the expectancy-value judgments model of uses and gratifications is its capacity for comparative analysis to explain differences in expectations and beliefs between different already accepted media technologies (e.g., mobile phone use vs. landline phone use) for different audiences (cf. McQuail, 2001).

Malhotra (2005) posed that the variables that moderate the effect of attitudes and intentions need to be identified and understood. Moderators that have been identified include motivation and ability, experience, prior knowledge, and mere exposure (Haugtvedt, 1997). According to Malhotra (2005) theories, such as the theory of reasoned action and the theory of planned behavior (the background theories of the expectancy-value judgments model of uses and gratifications), need to be modified to account for automatic habitual behavior, such as that engendered by past use.

The usefulness of the expectancy-value model of uses and gratifications to predict the adoption of a new technology is not sufficient. Because not all corresponding expectancy-value judgments clusters that might be important to a new media technology are known beforehand, one must solely rely on previously established gratification clusters of other (perhaps related) media technologies. Furthermore, the results of this study tentatively imply that within the expectancy-value model of uses and gratifications a person's attitude towards the intention to use a new media technology has no significant influence on intention. This finding supports the proposition that attitudes do not necessarily lead to intentions to act because they frequently fail to contain sufficient motivational content. That is, evaluations of the consequences of acting or of acting, per se, express one's liking towards a behavior but do not necessarily imply a motivational commitment to act (Bagozzi, 1992; Bagozzi & Kimmel, 1995).

Unified model of acceptance and use of technology. The unified model of acceptance and use of technology is most useful to supply general information on user's opinions about a technological innovation already present in the organization in terms of expectancies and conditions of use. The findings of this study imply that although statistically the unified model of acceptance and use of technology surpasses both the expectancy-value model of uses and gratifications and the model of media attendance in both explaining and predicting mobile communication technology behavior, the specific quality of the constructs of the unified model limits its generalizibilty beyond an organizational context. Therefore, employing the specific constructs of the unified model to explain and predict general media behavior might not be theoretically justifiable, unless the measures of the unified model are revalidated in the new context one wishes to use the unified model in.

According to Venkatesh et al. (2003), the measures for the unified theory of acceptance and use of technology should be viewed as preliminary and future research should be targeted at more fully developing and validating appropriate scales for each of the constructs with an emphasis on content validity, and then revalidating the model specified herein (or extending it accordingly) with new measures (p. 468). The findings of this study imply that the explanatory power of unified model can be improved by incorporating theoretical meaningful explanatory variables that could further explain the dynamics between the different constructs of the unified model of acceptance and use of technology. Parsimony - the need to identify factors that account for the most variance - is to be greatly valued (Burgoon & Buller, 1996), however not at the expense of explanatory power. Therefore, the unified model as it is originally defined by Venkatesh et al. is more useful to predict user's general opinions about expected use (e.g., opinions about the expected performance and required effort to use a particular technology) than to explain the motivations related to the continued and increased use of a particular media technology. This is because the unified model cannot explain the different underlying mechanisms such as how people come to learn of and choose to initially use a technological innovation (cf. Stafford et al. 2004, p. 265).

Model of media attendance. Although, the model of media attendance was originally proposed to explain the determinants of media technology usage in social cognitive terms, the findings of this study imply that the model of media attendance is also capable to explain the determinants of people's intention to adopt a new media technology. In terms of explaining and predicting media technology behavior, the results of this study showed that within the model of media attendance existing media technology use (e.g., using a mobile phone) is more likely to be explained by habit strength, and the intention to adopt new media technology (e.g., to intention to use mobile video phone) is more likely to be predicted by outcome expectations. This finding implies a reciprocal relationship between habit strength and expected outcomes. Once media use is more strongly determined by habituation, the effect of outcome expectations in determining people's media behavior may no longer have much influence because people are no longer aware of the relative importance of expected outcomes or no longer have expectations because the outcomes are already known. On the other hand, the results of this study show a strong effect of expected outcomes on prospective habit strength with regard to predicting the adoption of a new media technology. This finding implies that as long as media technology use is not fully habitualized, habit strength is causally determined by outcome expectations, which precede habit strength in time (LaRose & Eastin, 2004). Future research should more in depth investigate this reciprocal relationship, which requires a longitudinal research design.

The model of media attendance grounded in social cognitive theory offers some promising steps forward in the understanding of the underlying mechanisms that determine media technology behavior from both the perspective of explaining and predicting media behavior as well as from the perspective of validating and extending theory about the acceptance and use of media technology. More stringent follow-up tests of the model of media attendance extended to other media technologies and within different contexts of media use are needed to further state the degree of corroboration of the model of media attendance.

10.2 Limitations of the Study

Some limitations of this study should be acknowledged. First, data to test the three models were checked for normality. Because of skewness to either the upper end or the lower end of the distribution of several measures of the three tested models, a transformation was performed to correct skew both in the context to explain and predict mobile communication technology behavior. The transformations applied to correct skew could have caused an over-interpretation of the difference between the characteristics of the variables. Furthermore, in the expectancy-value judgments model to predict mobile video phone intention the indicators of novelty are closely related to the indicators of relaxation and to the indicators of affection/sociability. Also, in the model of media attendance to predict mobile video phone intention the indicators of activity outcomes are closely related to the indicators of status outcomes. This might reflect less discriminant validity of the constructs concerned.

Secondly, the measurement of novel and status outcomes as latent indicators to explain mobile phone use in the model of media attendance was limited in terms of reliability. Although the internal consistency of both novel and status outcomes has improved compared to the pre-test, the measures were still below aspiration level and were excluded from further analysis. Extended item batteries should be developed more specifically to match the media technology in question to gain a stronger operationalization of the latent constructs. Similarly, the measurement of facilitating conditions in the unified model of acceptance and use of technology was limited in terms of reliability. As a result it was not possible to legitimately compare the three models to explain mobile phone use in terms of explained variance.

Finally, to improve the fit of the model of media attendance to explain mobile phone use, post hoc modification indices suggested to correlate the error terms of habit strength with monetary outcomes, and self-reactive outcomes with both activity outcomes and deficient self-regulation. The covariance between the residual errors for habit strength and monetary outcomes is, in retrospect theoretically justifiable as it indicates a feasible reciprocal relationship between habit strength and expected outcomes. The relationship between self-reactive outcomes and deficient-regulation has already been hypothesized by LaRose and Eastin (2004) within the context of Internet usage, where self-reactive outcomes of Internet usage were positively related to Internet activity outcomes. Although, self-reactive and activity outcomes are theoretically distinct, the two outcome expectations are strongly related concepts, and it is therefore feasible that these measures have something specific in common. Additionally, in the context of Internet usage, LaRose and Eastin correlated the error terms between self-reactive outcomes and activity outcomes.

10.3 Implications for Using Models in Media Use Research

The insights gained in this study clearly show that both an empirical and theoretical evaluation and comparison of models are necessary to asses the statistical and substantive quality of a model. It is counterproductive to hold ‘statistical horse races’ to see what model brings about more explained variance and discard the ‘loser’ (Maddux, 1993). Models constructed in such a way as to maximize explained variance without the regard to the discreteness among variables that are needed to develop explanatory understanding cannot be viewed as being equivalent to those that show sensitivity with respect to such issues (Britt, 1997, p. 160). It is therefore suggested that the solution of the problem of how to choose among competing models should be a balancing act between maximizing empirical quality and maximizing theoretical quality. Good models are those that have confronted these options and have successfully engaged in this balancing act (cf. Britt, 1997). The presented quantitative and qualitative criteria in this study therefore can help to systematically asses both the empirical and theoretical quality of a model. Especially when a model is extended, modified or applied beyond its original context, the theoretical criteria to assess the quality of the model might not be neglected. It is far too easy to create a statistically significant model that will perform well for reasons that have nothing to do with being a good approximation of the phenomena of interest.

The most important implication that can be derived from the findings of this study is that the choice of a model to understand a particular media technology behavior should be determined foremost by the stage of development and diffusion the particular media technology is in. Depending on whether the media technology in question is an already well-accepted media technology or a new innovative media technology, an appropriate media use model should be selected to respectively explain and predict media technology behavior.

Although the discussed media use models in this study have all been used to explain and predict media technology behavior, the results of this study show that only the model of media attendance has proven to be capable to theoretically explain the dynamics of media technology behavior in both the context to explain existing media technology use and to predict the intention to adopt a new media technology.

In contrast to the two alternative models to understand media technology behavior, the theoretical core of the model of media attendance remains the same for all media technologies in both explaining and predicting media technology behavior. As the components of the model of media attendance are constructed to represent general mechanisms that determine human behavior, only the underlying indicators of the construct have to be reformulated in the context of the particular media technology of interest. Whereas in the expectancy-value judgments model of uses and gratifications for each particular media technology first a tailor-made list of expectancy-value judgments clusters have to be developed and validated before this particular media technology can be examined by the model. Likewise, because of the limitation in generalizibilty beyond its original context, the measures of the unified model of acceptance and use of technology also have to be revalidated first before the unified model can be used to examine a particular media technology that lies outside of the model's original scope.

In sum, based on the insights gained in this study, as well as consideration of the limitations of this study, it can be concluded that (a) the model of media attendance should perform well in both explaining and predicting media technology behavior due to the model's underlying interrelated and reciprocal mechanisms of general human behavior; (b) the expectancy-value judgments model of uses and gratifications should perform well in explaining existing media technology behavior in terms of beliefs and expectations; and (c) the unified model of acceptance and use of technology should perform well in supplying general information on user's opinions about a media technological innovation in terms of expectancies and conditions of use.

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Samenvatting

In dit proefschrift staan de sociaal-psychologische determinanten van het gebruik en de adoptie van mobiele communicatiemiddelen centraal. Op basis van kwalitatieve en kwantitatieve criteria zijn drie sociaal-psychologische modellen met elkaar vergeleken met als doel vast te stellen welk van de drie modellen zowel empirisch als theoretisch het beste in staat is om mobiel communicatiegebruik en -adoptie te verklaren en te voorspellen.

Wereldwijd zijn in de laatste tien jaar de technologische ontwikkelingen op het gebied van telecommunicatie sneller gegaan dan in de afgelopen honderd jaar. Mobiele communicatiemiddelen zijn bijna volledig geïntegreerd in het dagelijks leven voor zowel persoonlijk als zakelijk gebruik. De mobiele telefoon als meest prominent voorbeeld van mobiele communicatietechnologie is meer dan alleen een middel om mobiel mee te telefoneren. De mobiele telefoon heeft zich in de laatste jaren ontwikkeld tot een nieuw type informatie- en communicatiemiddel met een verscheidenheid aan diensten en technologische mogelijkheden zoals bijvoorbeeld SMS, internet, navigatie, fotografie, videotelefoon, MP3-speler, en het ontvangen van radio- en televisieprogramma's.

Inzicht in het gedrag van de mobiele communicatiegebruiker is voor de mobiele communicatie-industrie van het grootste belang om accuraat te kunnen reageren om het steeds veranderende gedrag van hun consumenten. Inzicht in de behoeften en wensen van mensen is noodzakelijk om producten en diensten aan te kunnen bieden die ook daadwerkelijk worden gebruikt. Voor zowel de mobiele communicatie-industrie als vanuit een wetenschappelijk perspectief is het gedrag van de mobiele communicatieconsument van belang om beter inzicht te krijgen in het proces van technologische innovatie, diffusie en het gebruik van mobiele communicatiemiddelen.

In het uitgevoerde onderzoek naar de sociaal-psychologische determinanten van het gebruik en de adoptie van mobiele communicatiemiddelen is vooral de nadruk gelegd op het vergelijken van drie prominente gedragsmodellen die mediagebruik en -adoptie kunnen verklaren en voorspellen; 'the expectancy-value judgments model of uses and gratifications' (Babrow & Swanson, 1988), 'the model of media attendance' (LaRose & Eastin, 2004), en 'the unified model of acceptance and use of technology' (Venkatesh et al., 2003).

Een vergelijking van de theorieën die ten grondslag liggen aan de drie modellen laat zien dat er verschillende theoretische verbanden en overeenkomsten tussen de drie modellen bestaan wat betreft de centrale processen en fenomenen die mediagebruik en -adoptie verklaren en voorspellen. Echter, ondanks de grote overeenkomsten tussen de drie modellen met betrekking tot de theoretische achtergrond beschrijft elke model verschillende determinanten die het gedrag van mediagebruik en -adoptie verklaren en voorspellen. Om een antwoord te kunnen geven op de vraag welk model het meest geschikt is om zowel empirisch als theoretisch mediagebruik en -adoptie te verklaren en te voorspellen, is op basis van kwantitatieve en kwalitatieve criteria onderzocht welk van de drie modellen het beste in staat is om mobiel telefoongebruik te verklaren (mediagebruik) en de intentie om mobiel videotelefoon te gaan gebruiken te voorspellen (media-adoptie). Met mobiel videotelefoon kan je niet alleen met iemand anders praten, maar kan je de ander ook zien.

Respondenten uit een bestaand landelijk panel ($N = 1299$) beheerd door een commercieel onderzoeks- en consultancybureau zijn via email uitgenodigd om deel te nemen aan de online survey. Middels een gestratificeerde a-selecte streekproef met demografie, mobiel telefoongebruik en -ervaring als strata zijn de 964 respondenten (74,21%) verdeeld in drie groepen. De ingevulde vragenlijsten van groep 1 ($n = 310$) zijn gebruikt om het expectancy-value judgments model of uses and gratifications te toetsen in de context van mobiel telefoongebruik en het model of media attendance te toetsen in de context van mobiel videotelefoon-adoptie. De ingevulde vragenlijsten van groep 2 ($n = 334$) zijn gebruikt om het model of media attendance te toetsen in de context van mobiel telefoongebruik en het unified model of acceptance and use of technology te toetsen in de context van mobiel videotelefoon-adoptie. De ingevulde vragenlijsten van groep 3 ($n = 320$) zijn gebruikt om het unified model of acceptance and use of technology te toetsen in de context van mobiel telefoongebruik en het expectancy-value judgments model of uses and gratifications te toetsen in de context van mobiel videotelefoon adoptie.

Voor het empirisch toetsen van de drie modellen is gebruik gemaakt van 'structural equation modeling' (SEM). SEM is een statistische methode waarbij onderliggende causale relaties tussen variabelen gerepresenteerd worden in een serie regressievergelijkingen. Deze regressievergelijkingen worden als geheel geanalyseerd om na te gaan in hoeverre de gepostuleerde relaties tussen de variabelen overeenkomen met de empirisch verzamelde data. Indien de 'fit' tussen het model en de empirische data niet adequaat is, moet het model worden verworpen.

Op basis van de kwantitatieve en kwalitatieve resultaten van het uitgevoerde onderzoek kan worden geconcludeerd dat:

(a) zowel een empirische als ook een theoretische evaluatie en vergelijking van causale modellen noodzakelijk zijn om de statistische en inhoudelijke kwaliteit van een model te bepalen. In het bijzonder wanneer een model is uitgebreid, veranderd of toegepast buiten de oorspronkelijke context, mogen de theoretische criteria om de kwaliteit van een model te bepalen niet uit het oog worden verloren;

(b) vooropgezet dat men bekend is met de eigenschappen van een nieuwe technologie (bijvoorbeeld doordat men er iets over heeft gehoord of gelezen) is iemands positieve of negatieve houding ten aanzien van een nieuwe technologie minder van invloed op de intentie om deze technologie te gaan gebruiken dan de verwachtingen ten aanzien van de technologie en de invloed van familie en vrienden;

(c) wanneer mediagebruik sterker wordt bepaald door gewoontegedrag zal het effect van uitkomstverwachtingen minder van invloed zijn op iemands mediagebruik omdat men zich dan niet langer meer bewust is van het relatieve belang van uitkomstverwachtingen of omdat er geen uitkomstverwachtingen meer zijn omdat de uitkomsten al bekend zijn;

(d) welke determinanten van het gebruik en de adoptie van mobiele communicatiemiddelen het meest van belang zijn, hangt sterk of van de fase waarin een bepaalde technologie zich bevind. Bijvoorbeeld bij het verklaren van een volledig geaccepteerde mediatechnologie zoals de mobiele telefoon spelen met name intenties en gewoonte een rol. Terwijl bij de adoptie van een nieuwe innovatieve technologie zoals mobiel videotelefoon met name uitkomstverwachtingen een rol spelen.

(e) afhankelijk van de ontwikkelings- en verspreidingsfase van een bepaalde technologie moet er een keuze worden gemaakt voor een bepaald model dat mediagebruik kan verklaren of media-adoptie kan voorspellen. De meeste onderzoekers zijn nog steeds op zoek naar een model dat alles kan verklaren (zowel mediagebruik als –adoptie in alle fasen). De resultaten van dit onderzoek geven echter aan dat men gerichter een model moet kiezen.

Als antwoord op de vraag welk model het meest geschikt is om zowel empirisch als theoretisch mediagebruik en -adoptie te verklaren en te voorspellen kan op basis van de resultaten van dit onderzoek samenvattend worden geconcludeerd dat:

(a) het model of media attendance meer dan de andere twee modellen geschikt is om zowel mediagebruik te verklaren als media-adoptie te voorspellen omdat dit model het meest gedetailleerd de onderliggende theoretische mechanismen beschrijft die van invloed zijn op iemands mediagebruik en –adoptie;
(b) het expectancy-value judgments model of uses and gratifications met name geschikt is om mediagebruik te verklaren in termen van opvattingen en verwachtingen ten aanzien van bestaand mediagebruik;
(c) het unified model of acceptance and use of technology met name geschikt is in het weergeven van algemene opinies ten aanzien van nieuwe technologische innovaties in termen van verwachtingen en gebruikscondities.

Op basis van de inzichten verkregen uit dit onderzoek kan gesteld worden dat het contraproductief is om bij het vergelijken van modellen te kiezen voor het model met de hoogste statistische verklaarde variantie. Modellen die zodanig zijn geconstrueerd dat de verklaarde statistische variantie maximaal is zonder rekening te houden met de afzonderlijke variabelen die nodig zijn om inhoudelijk een bepaald fenomeen of proces te begrijpen, hebben minder theoretische verklaringskracht dan modellen waarbij naast de statistische verklaarde variantie ook rekening wordt gehouden met de inhoudelijke verklaringskracht van de afzonderlijke variabelen. Het is niet moeilijk om een model te construeren dat statistisch significant is, maar inhoudelijk niets van doen heeft met het fenomeen of proces dat men wil verklaren of voorspellen. De keuze voor een bepaald model moet dan ook een balans zijn tussen maximale statistische en maximale inhoudelijke verklaringskracht. De in dit proefschrift gepresenteerde kwantitatieve en kwalitatieve criteria kunnen derhalve helpen bij het systematisch vaststellen en vergelijken van de empirische en de theoretische kwaliteit van modellen.