USING USER PERSONALITY TO EXPLAIN THE INTENTION-BEHAVIOR GAP AND CHANGES IN BELIEFS: A LONGITUDINAL ANALYSIS

Completed Research Paper

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Abstract

The research reported in this article intends to investigate whether individuals a) update degrees of beliefs over time and b) transfer behavioral intentions into adoption behavior in a different manner based on their personality. Therefore, the personality trait dispositional resistance is discussed within the Integrative Framework of Technology Use. Results of an empirical longitudinal analysis (N=145) show that individuals update their beliefs based on prior beliefs and usage behavior differently in accordance with their personality. Results also reveal that individuals transfer behavioral intentions into adoption behavior differently based on their personality. Hence, we discuss our contributions to technology adoption research by highlighting the importance of personality traits when investigating technology-related beliefs and behavior over time. Results also include an assessment of the findings' practical relevance by identifying which individuals maintain negative beliefs over time and by identifying the high extent of technology usage as a possibility for overcoming negative beliefs.

Keywords: Individual differences, Personality traits, User behavior, Moderating effect, Longitudinal research, Dispositional resistance, Technology adoption, Belief-update theory, Intention-behavior gap, Integrative framework of technology use

Introduction

Imagine a new technology is available (e.g., e-books, video conferencing software) but some individuals are not completely convinced and think negatively about it. Some days later, they watch TV advertisements or listen to a discussion of friends enthusing over this new technology. For some of them, this situation might bring a shift from their originally rather negative beliefs to more positive ones. However, others will remain unimpressed by such situations and continue to have negative beliefs. Some of them will even continue having negative beliefs after the technology re-launches its concept and therewith enhances its usefulness and ease of use. Applying this situation to concrete technology usage contexts when information technology (IT) is introduced into households (e.g., e-books, online social networks) or workplaces (e.g., video conferencing software, messenger), some individuals might have positive or negative beliefs about a new technology. Those with negative beliefs are particularly challenging as they do not use the technology as expected or even not at all (Lapointe and Rivard 2005; Kim and Kankanhalli 2009; Polites and Karahanna 2012). Overcoming negative beliefs is consequently an objective for IT project management in the workplace to ensure the success of an implemented technology, as well as an objective for IT sales managers when focusing on selling new technologies to households. In the latter context, it is important to overcome negative beliefs of end-users so that they buy products (e.g., smartphones, e-books) or adopt technologies (e.g., online social networks). However, as the introductory example illustrates, some individuals quickly and easily change the extent and degree of their beliefs, from more negative into positive ones, as well as their usage or adoption behavior, while others retain their negative beliefs even after the technology is redesigned accordingly.

In order to explain this situation, and with it how and why individuals change the extent of their negative or positive beliefs about a particular form of IT, this research proposes a longitudinal individual-focused explanation of changing beliefs and behavior. Here, psychology research suggests that individuals' views are in accordance with their personality (McCrae and Costa 2001). Hence, personality might be the reason why some individuals facilitate more easily changes in the degree of their beliefs from rather negative to positive, or vice versa, whereas others are highly consistent in their beliefs. In order to examine this against a specific personality trait that is the source of such changes, Oreg (2003) proposes concentrating on the personality trait of dispositional resistance which reflects how some individuals are predisposed to resist external changes (e.g., in organizations) as well as detecting internal changes in an individual's mind and view which mean that they change the extent of their beliefs less often.

Applied to information systems research and the situation described in the beginning, beliefs are basically updated over time based on prior beliefs and behavior, as suggested by the integrative framework of technology use (IFTU; Kim and Malhotra 2005). Additionally, we propose that the mode of a technology-related belief-update is based on a user's personality, by theorizing that beliefs are updated differently from person to person to align with their personality in general and dispositional resistance in particular. Consequently, we will address the following initial research question:

> *RQ1: How does user personality in terms of dispositional resistance influence the change of technology-related beliefs over time?*

Moreover, one might also use the opening example to illustrate that individuals transfer intentions into behavior differently by imagining that two individuals share the same behavioral intention to register with online social networks (OSNs) but only one actually does so. Based on the general assumption of technology acceptance literature, individuals form behavioral intentions which lead to specific behavior. However, the example shows that individuals have different thresholds which have to be met in order to transfer hypothetical intentions into adoption behavior and hence leave behind the status of being a non-adopter. As a consequence, some individuals with high behavioral intentions have not adopted a technology over time, whereas others are adopters even when they have a comparable low behavioral intention. Though this sounds like a rare occurrence, it is widespread and known as intention-behavior gap in IS research (Bhattacherjee and Sanford 2009). It reflects the phenomenon that not all individuals transfer these intentions into actions equally. Prior research identifies that only 35 out of 100 individuals show adoption behavior that is aligned with their intentions (Taylor and Todd 1995; Venkatesh et al. 2003). Thus, despite high behavioral intentions some individuals do not adopt the technology while others do so. This is due to the fact that individuals transfer intentions into behavior in accordance with their personality, so that the intention-behavior relation is moderated by a user's personality (Ajzen 2002b). This reflects the fact that the threshold above which the hypothetical intentions are transformed into actual behavior varies based on personality (Allen et al. 2005), so that some individuals resist adopting new forms of behavior more frequently than others. Since this is reflected by the personality trait of dispositional resistance (Oreg 2003), the trait is again used as an example of user personality in order to examine whether or not individuals transfer intentions into behavior. Hence, in order to understand how behavioral intentions regarding the adoption of IT are transferred into action over time, the second research question of our paper is:

> *RQ2: How does user personality in terms of dispositional resistance influence the intention-behavior relation over time?*

Based on the described challenges, these research questions also align with calls made in recent research articles. As IS research examines technology usage from a static perspective, Benbasat and Barki (2007) call for an investigation into dynamic interplays of beliefs, intentions, and behavior over time. Moreover, Devaraj et al. (2008) and McElroy et al. (2007) encourage researchers to integrate personality traits into different streams of IS research, such as the updating of beliefs or the transferring of behavioral intentions into behavior. In particular, Brown et al. (forthcoming) call for research including personality as a moderator in technology acceptance research, because "*different types of individuals [...] could react differently, thus resulting in personality playing a key moderating role*" (p. 11). Also, Bhattacherjee and Sanford (2009) call for future research addressing the intention-behavior gap, which here is addressed in particular by the second research question.

Based on an empirical longitudinal analysis with 145 individuals, our results indicate that the personality trait of dispositional resistance does indeed have an influence on the belief update and hence whether or not individuals change the degree of their beliefs. Moreover, our results also reveal that dispositional resistance influences whether or not individuals transfer intentions into adoption behavior.

To address these calls and to answer both research questions, the remainder of this article is as follows. First, current information about changing beliefs and behavior is provided. Afterwards, the hypotheses are developed in order to propose a research model that helps us answer our research questions. After explaining our research methodology, the research results are presented. Subsequently, for each moderation effect the strength of effect is highlighted before we discuss the research results.

Literature Background and Hypotheses Development

In the attempt to examine dynamic interplays in the change of beliefs, intentions, and behavior over time, the integrative framework of technology use (Kim and Malhotra 2005) provides the underlying theoretical arguments that will lead to the development of our hypothesis regarding the impact of the dispositional resistance personality trait on IT acceptance over time. Thus, we will first introduce the integrative framework of technology use and follow this with a discussion of individual differences and the acceptance of IT over time. Based on this discussion, we will propose three detailed hypotheses about the moderating influence of a user's personality – in terms of dispositional resistance – on changing beliefs and the intention-behavior gap.

Integrative Framework of Technology Use

The integrative framework of technology use (IFTU, Kim and Malhotra 2005) attempts to explain the dynamic interplay of beliefs, intentions, and behaviors related to the technology acceptance phenomena. The framework is applied in the form of a two-wave panel model with the technology acceptance model (TAM) as the underlying reason-oriented action mechanism (see Figure 1). It suggests that beliefs related to a particular technology, such as perceived usefulness and perceived ease of use, influence behavioral intentions. In this context, perceived usefulness is defined as the degree to which an individual believes that the usage of a technology is perceived as useful. Perceived ease of use is defined as the degree to which a technology is perceived to be free of effort (Davis 1989). Afterwards the resulting behavioral intention becomes a driving force in translating these intentions into behavior. Such intention-based models like IFTU or TAM, which consider behavioral intentions as antecedent to behavior, link the waves of t_1 and t_2, by theorizing that the intention of t_1 determines behavior in t_{1-2}.

Next to the described mechanism, IFTU includes the sequential updating of judgments mechanism in terms of belief update theory (see Figure 1). The theory posits that beliefs do not arise out of nothing but are developed from prior beliefs. Thus prior beliefs are considered to be an anchor that is gradually updated after receiving new information at a later point in time. This is observable in particular in consumer research (Hogarth and Einhorn 1992; Bolton 1998), where consumers process incoming information by updating all prior beliefs, which are affected by new information.

In addition to this, feedback mechanism in terms of self-perception theory (Bem 1972) is considered by IFTU to explain the formation of beliefs based on behavior (see Figure 1). Self-perception theory is developed in order to explain inconsistencies in the widespread cognitive dissonance theory (Festinger 1957) and thus contradicts the widespread assumption that beliefs shape behavior by instead considering behavior to be the cause of beliefs. In more detail, self-perception theory proposes that the formation of beliefs is based on prior and current behavior. Therefore, it is theorized that individuals have not formed beliefs up to the point in time when they are asked to evaluate that behavior. Resulting beliefs are derived from observing the individual's own prior and current behavior, with the result that beliefs will be biased by the extent of current and prior usage behavior.

In summary, IFTU, as illustrated in Figure 1, combines self-perception theory (purple line), belief update theory (green line), and TAM (black line) including the intention-behavior relation (blue line) in order to explain technology acceptance decisions over time. Nonetheless, only linear relationships between beliefs, behavioral intentions, and behavior are used. Kim (2009) identifies these exclusively linear relationships as a shortcoming of IFTU and indicates that moderating effects are absent. These effects might take into account that different types of individuals form and change beliefs or transfer intentions into behaviors differently. To overcome this limitation, Brown et al. (forthcoming) call for research that integrates individual differences, such as personality traits, as moderators into models and theories in order to clarify how individuals with different personalities change beliefs and transfer intentions into behavior over time. This will be discussed in the following sub-sections.

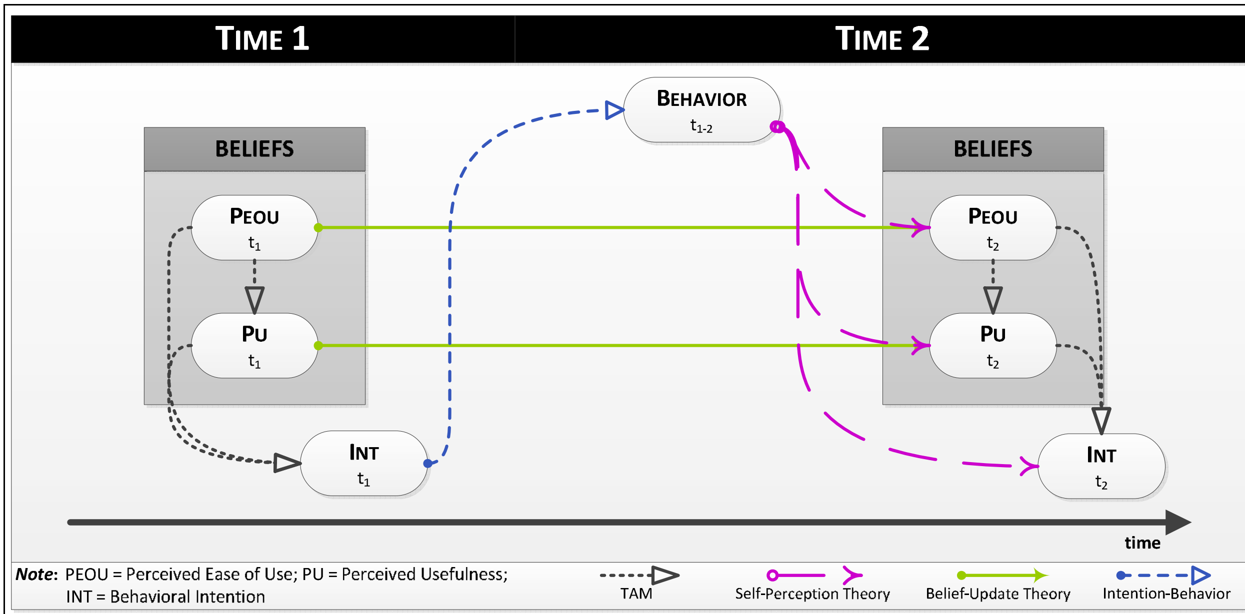

Figure 1. Intention-Behavior Relation, Belief Update, and Self-Perception Theory

Individual Differences, Personality Traits, and Dispositional Resistance

Individual differences represent aspects that make one individual different from others, such as age, gender, tenure, or predisposed personality traits (Thatcher and Perrewé 2002). Such differences have been researched for a long time. Among others, Agarwal and Prasad (1999) investigate the influence of tenure, level of education, and experience on beliefs or Venkatesh et al. (2003) concentrate on gender, age, and experience. More recently, researchers pay attention to predisposed personality traits as one dimension of individual differences, which influence beliefs and behavior (see Maier 2012 for a review). Such personality traits depict constant patterns of thoughts, feelings, and behavior across diverse situations that distinguish individuals from each other (McCrae and Costa 2006). These have the characteristic of being stable across situations and times (Ajzen 2005) and are formed independently of any technology (Agarwal and Prasad 1998; Venkatesh 2000).

As we aim to provide an explanation of the influence of user personality on belief updates over time and to discuss what hinders individuals from transferring intentions into behavior, we have to identify a trait that fits the needs of our research objective (Paunonen and Ashton 2001). After screening IS and psychological research for a trait that can be used for our purpose, we identify the trait of dispositional resistance, which is defined as an inclination to resist any kind of changes and includes that individuals change their views, minds, and behaviors differently (Oreg 2003). As no other trait exists addressing this disposition directly (Oreg 2003, p. 680), as the disposition has a high accuracy of fit with our research objective (Paunonen and Ashton 2001), and as it seems to be of great value for providing a new contribution to the question of whether or not individuals change beliefs on the one hand and transfer behavioral intentions into actual behavior on the other hand, the personality trait of dispositional resistance is used in this research as an example of user personality. It is described in the following paragraphs in more detail.

In order to focus on the multiple predisposed causes for resistance to change, Oreg (2003) proposes four dimensions that influence individuals' overall dispositional resistance. The first dimension, called routine seeking, reflects individuals' degrees of preference for stable environments, whereby individuals' oppose abandoning habits and favor fewer new inputs from the environment (Oreg 2003). The second dimension is termed emotional reaction, and indicates the extent of individuals' levels of stress when confronted with upcoming changes (Oreg 2003). The third dimension is called short-term focus, and concentrates on the individuals' degree of concern with the short-term inconveniences of a change while not considering its possible long-term advantages (Oreg 2003). The fourth dimension, cognitive rigidity, reflects individuals' disinclination to take account of innovative ways, solutions or perspectives, which derive from individuals' stubbornness or unwillingness (Oreg 2003). Together, these dimensions represent the personality trait of dispositional resistance.

This trait has been used in IS related research recently. In this process, Polites and Karahanna (2012) integrate the trait dispositional resistance within their research model investigating the influence of inertia, habit, and switching costs on technology acceptance as control variable. Thereby, an impact of dispositional resistance on inertia, which is understood as some form of attitude towards an IT-induced change in the implementation process, is empirically verified, whereby no significant direct impact on perceived ease of use, perceived usefulness, subjective norm, and behavioral intentions could be verified. Nonetheless, two other articles verify direct effects of dispositional resistance on perceived ease of use and perceived usefulness using empirical data (Nov and Ye 2008; Maier et al. 2011).

Beside the attempts at evaluating the direct impact of dispositional resistance on the dynamic interplay of beliefs, intentions, and behavior, research also suggests considering traits as a moderating factor (Allen et al. 2005). Consequently, this article uses the trait dispositional resistance as a moderator in the longitudinal IFTU in order to reveal whether resistant individuals change beliefs as well as transfer intentions into behavior in the same manner as less resistant individuals.

The Moderating Influence of Dispositional Resistance on Belief Updates

The updating of beliefs is a particular focus of continuance technology usage research (Bhattacherjee and Premkurnar 2004; Kim and Malhotra 2005; Kim 2009). These research articles suggest that current beliefs (t_2) are mainly affected by prior beliefs (t_1). This has been empirically tested for the beliefs usefulness and ease of use by Kim and Malhotra (2005). This means that most of the individuals considering a technology as useful or easy to use in t_1 will also have positive beliefs in terms of usefulness or ease of use in t_2. In contrast, most individuals with negative beliefs in t_1, such as low levels of usefulness or ease of use, also have negative beliefs in t_2. Nonetheless, these articles only focus on linear relationships between a belief in t_1 and the same belief in t_2 and consequently neglect moderating effects, which is explicitly mentioned as a limitation by Kim (2009, p. 529). Thus it is not possible to show how different types of individuals update their beliefs over time, even if it is known that individuals form and update their beliefs based on personality (Devaraj et al. 2008, Oreg 2006).

In order to address the question of whether some individuals update their beliefs more frequently than others and hence change the extent of their beliefs, we discuss the impact of dispositional resistance on belief updates. Dispositional resistance suggests that some individuals have more consistent beliefs over time than others. As resistant individuals are characterized as dogmatic, closed-minded, and cognitively rigid (Oreg 2003), they have consistent views over time and hence do not easily or often update the degree of their belief from positive to negative, or vice versa. This suggests that resistant individuals do not update the degree of their beliefs frequently, and consequently have more consistent beliefs than less resistant individuals. In contrast, less resistant individuals are characterized as open-minded, less dogmatic, and less cognitively rigid, so that they more frequently and regularly update the degree by which their beliefs change.

After discussing the effect of dispositional resistance on belief update in general, we now concentrate in more detail on the influence of the personality trait on the two beliefs, perceived usefulness and perceived ease of use. For perceived usefulness, this implies that resistant individuals who perceive a technology as less useful in t_1 will also attribute a low usefulness to this technology in t_2, whereas every resistant individual perceiving the technology as useful in t_1 will subsequently maintain this positive belief. In contrast, less resistant individuals update their degree concerning perceived usefulness more often. When a technology is perceived as useless by them in t_1, they might update their perceived usefulness afterwards and consider it as more useful in t_2 compared to the prior perceived usefulness in t_1. The situation described here for perceived usefulness arises in a comparable manner for perceived ease of use, to the extent that resistant individuals update the degree in perceived ease of use less often than less resistant individuals. Hence, resistant individuals will be more consistent concerning their degree in perceived ease of use over time. Based on this, the following hypotheses are derived:

> *H1a: Dispositional resistance moderates the influence of perceived ease of use in* t_1 *on perceived ease of use in* t_2 *to the extent that resistant individuals change the degree in their belief less often.*
>
> *H1b: Dispositional resistance moderates the influence of perceived usefulness in* t_1 *on perceived usefulness in* t_2 *to the extent that resistant individuals change the degree in their belief less often.*

The Moderating Influence of Dispositional Resistance on Self-Perceptions

IFTU states that beliefs are not solely updated based on prior beliefs but also based on prior and current behavior. Recent research validates this feedback mechanism empirically, so that beliefs such as perceived usefulness or perceived ease of use are influenced by the extent of technology usage behavior (Kim and Malhotra 2005). This means that individuals using a technology to a large extent report positive beliefs more often than individuals using a technology less often. Nonetheless, research reveals that some individuals exhibit inconsistencies between beliefs on the one side and behavior on the other (Kraus 1995), whereby these inconsistencies are explicable when taking individual differences into account (Gangestad and Snyder 2000). In order to consider this knowledge, this research investigates the influence of user personality in terms of dispositional resistance on the feedback mechanism and hence on the influence of usage behavior on beliefs.

Prior research assumes that individuals update their beliefs and intentions based on their usage behavior (Kim 2009). Nonetheless, these experiences, which are made while using a technology, are processed differently based on user personality, since more resistant individuals react to such a feedback mechanism with more reservation (Linderbaum and Levy 2010). Hence, resistant individuals have to gain considerably more experience by using the technology more frequently in order to update or change the degree of their beliefs and behavioral intentions to the same extent as less resistant individuals. This suggests that dispositional resistance moderates the influence of usage behavior on beliefs and behavioral intentions respectively.

For individuals who seldom use a technology, we theorize that less resistant individuals have more positive beliefs and higher intentions than resistant ones. This is due to the fact that less resistant individuals have high levels of self-esteem and self-confidence, so their optimistic attitude is reflected within more positive beliefs and higher intentions – even if the technology is seldom used– compared to more resistant individuals (Oreg 2003). In particular the combination of low usage extents and negative technology-related beliefs that dominate an individual's thought processes (Ito et al. 1998) result in situations in which particularly resistant individuals will retain negative beliefs over time. Consequently, resistant individuals will not develop more positive belief or behavioral intention as easy as optimistic and less resistant individuals. On the negative side, individuals using a technology frequently have much more possibilities to update beliefs and behavioral intentions based on their frequent usage behavior. Hence, highly resistant individuals have several possibilities to replace negative beliefs and intentions with positive ones based on the high usage extents and the response to the whole experience. This holds also true for less resistant individuals using a technology frequently. However, less resistant individuals are already more likely to have positive beliefs and high behavioral intentions based on their optimism, to the extent that this effect is of particular importance for highly resistant individuals.

This situation can be seen in more detail, regarding the belief's perceived usefulness and perceived ease of use as well as behavioral intentions. Summing up, we assume that high behavioral intentions and more positive beliefs in terms of usefulness and ease of use can be either seen by individuals using a technology frequently or by less resistant individuals using a technology rarely. Compared with this, individuals with low technology usage extent form more negative beliefs and develop lower behavioral intentions when highly resistant, so that we hypothesize:

> *H2a: Dispositional resistance moderates the relation between usage behavior and perceived ease of use, to the extent that less resistant individuals have a higher perceived ease of use when using a technology less often than resistant ones.*
>
> *H2b: Dispositional resistance moderates the relation between usage behavior and perceived usefulness, to the extent that less resistant individuals have higher perceived usefulness when using a technology less often than resistant ones.*
>
> *H2c: Dispositional resistance moderates the relation between usage behavior and behavioral intention, to the extent that less resistant individuals have higher behavioral intentions when using a technology less often than resistant ones.*

The Moderating Influence of Dispositional Resistance on the Intention-Behavior Relation

Existent technology usage models share the fact that they are intention-based models (Davis 1989; Venkatesh and Brown 2001; Venkatesh et al. 2003). They include the assumption that individuals have behavioral intentions to perform a certain behavior and subsequently transfer them into actions. However, most of these models only use behavioral intention as a dependent variable (Bhattacherjee and Premkurnar 2004). Nonetheless, previous research identifies inconsistencies between behavioral intentions and behaviors and names this phenomenon intention-behavior gap (Bhattacherjee and Sanford 2009) as it is expected that behavioral intentions and behavior have a greater coherence.

This gap occurs as only some individuals with high intentions transfer them into behavior, whereas others resist and maintain the status quo regardless of their strong intentions. One crucial factor as to whether or not intentions are transferred is an individual's personality (Ajzen 2002b; Allen et al. 2005). For the trait dispositional resistance, we assume that the threshold when individuals transfer intentions into behavior is higher for resistant ones. In other words, less resistant individuals already transfer lower intentions into behavior. This is due to the fact that less resistant individuals are not afraid of the inconvenience associated with changing behavior in the short-term, so that they transfer intentions into behavior more frequently (Oreg 2003). On the negative side, resistant individuals react in an emotionally stressed manner when confronted with new possibilities and thus seek stable routines (Oreg 2003). They need higher behavioral intentions to transfer hypothetical intentions into behavior. Hence, we assume that less resistant individuals transfer behavioral intentions into behavior even when these intentions are lower compared to resistant individuals. Thus, we hypothesize that:

> *H3: Dispositional resistance moderates the relation between behavioral intentions and behaviors to the extent that less resistant individuals transfer already lower intentions into adoption behavior, whereas the adoption behavior of highly resistant individuals is solely the result of highly pronounced intentions.*

Empirical Evidence

Research Methodology

This research intends to examine the influence of a specific personality trait on changing beliefs as well as the transformation of behavioral intentions into behavior over time. In order to answer both research questions in one study, we have to use a certain type of technology. The first requirement for that technology is voluntariness concerning the adoption decision, because only in voluntary usage settings do individuals have the choice to decide whether or not behavioral intentions will be transferred into technology usage. Here, Brown et al. (2002) show that in mandated settings individuals transform intentions into behaviors because they have to do so, whereas in voluntary settings, individuals are free in their choice of transforming intentions into behaviors. Hence, the behavioral-intention gap is of particular importance in voluntary technology usage settings. Second, the technology should be well-known by individuals of all ages either as an adopter or not, so that a greater number of individuals have an opinion about the technology as well as having made a decision whether or not to use the technology. Third, the technology should be used by adopters to a different degree in order to examine the influence of behavior on beliefs as suggested by self-perception theory. Fourth, in order to observe belief updates and hence attaching different beliefs to distinct dates based on experience and information, the technology should be one that attracts attention in the press and a lot of information should be provided across different channels. Among other considerations, if we cannot account for these four preconditions before choosing a technology, we cannot answer both research questions within one article. Based on these four preconditions we made the decision to examine the research questions in the context of the online social network Facebook. Online social networks are generally well-known to a broad public and are used voluntarily, so we can investigate the intention-behavior gap. Moreover, the media presents an account of online social networks in both a positive and negative manner, so that the beliefs of individuals can change between these two points in time. Among others, negative press focuses on privacy and security policies or the fact that online social networks become a symbol of stress (e.g., Maier et al. 2012). In contrast to that, positive news describes the potential of using online social networks to coordinate events (e.g., Khan and Jarvenpaa 2010). Furthermore, Facebook re-launches user profiles by introducing timeline as the Facebook profile. Such changes increase the probability that at least some individuals change their views and hence that we can investigate whether or not the degree in beliefs are updated in accordance with the personality trait of dispositional resistance. The usage of online social networks is also in alignment with the call by Brown (2008) for a focus on researching online social networks while examining beliefs and behavior in voluntary usage settings at the individual level.

After determining to use Facebook as the underlying research topic for examining the research questions, we had to capture the data of Facebook users and non-users with distinct backgrounds. Therefore, we conducted two online surveys in September 2010 and September 2011. Participants were invited via email to participate in our study. The emails were collected over the last years using two different methods. First, individuals had the possibility of subscribing their email address on our university page so as to participate in forthcoming surveys. These individuals are mainly current or former students or individuals interested in our research. Second, we conducted several surveys related to different issues in the past. Among others, a large number of individuals participate each year in our surveys on computer personnel-related issues, such as turnover behavior. These participants were asked at the end of each survey whether or not they could subsequently be contacted by email for future surveys. Hence, the email list includes individuals of all age groups and from different educational backgrounds.

Based on this panel, we invited a representative sample of 500 individuals to take part in the longitudinal survey for this article. Each individual was invited once only via email to prevent bias participants by multiple incoming emails and not to exert pressure on participants. Each email includes a link which could be used only once, thus ensuring that nobody could take part several times. In order to increase response rate we raffled off three iPads in September 2010. For the second survey in September 2011 we only invited individuals who took part in the first survey. Consequently, 212 individuals again received an email with a link to the second survey, and again three iPads were raffled off amongst the participants. In the end, 145 individuals filled out both surveys completely.

Table 1 breaks down the demographics of our data sample, and shows that more men participated than women. The mean value of the age of the participants is 39.5 years.

Table 1. Demographics of the 145 participants

Demographics of the 145 participants										
Gender		Age								
Male	Female	<25	25-29	30-34	35-39	40-44	45-49	50-54	55-59	>59
62.1%	37.9%	10.3%	24.2%	10.3%	6.9%	10.4%	9.6%	13.1%	8.3%	6.9%

In addition, 58.4 percent of the participants indicated that they were a member of Facebook in September 2010 (t_1) as well as September 2011 (t_2). In contrast, 28.3 percent were not registered in Facebook at either of those times. The remaining 13.3 percent changed their behavior during the time period under investigation, so that 8 percent decided to register in Facebook after September 2010 (t_1), whereas 5.3 percent decided to unregister from Facebook after the first questionnaire.

Measures

Dispositional Resistance is measured with the original dispositional resistance scale suggested by Oreg (2003), which is validated in multiple research articles and cultural environments (Oreg et al. 2008) and consists of 17 items. In order to capture the heterogeneous causes of individuals' dispositional resistance, the scale includes four sub-scales. The scale routine seeking includes five items, such as "I like to do the same old things rather than try new and different ones". "When things don't go according to plans, it stresses me out" is one exemplary item to consider individuals' emotional reaction. Short-term thinking includes among others the item "Once I've made plans, I'm not likely to change them" and the forth scale cognitive rigidity includes items, such as "My views are very consistent over time". For descriptive purposes we remark that the coefficient alpha is high ($\alpha = 0.91$). To capture this personality trait, we utilized a 7-point Likert scale (1 = strongly agree, 7 = strongly disagree).

Beliefs and Behavioral Intentions are measured with items suggested by Davis (1989). The scale for behavioral intentions includes four items, such as "I intend to use Facebook in future" ($\alpha = 0.95$ (t_1); $\alpha = 0.96$ (t_2)). To capture perceived usefulness, four items are used ($\alpha = 0.96$ (t_1); $\alpha = 0.95$ (t_2)). Among others, participants are asked to rate statements, such as "Overall, I consider Facebook as useful". Perceived ease of use ($\alpha = 0.80$ (t_1); $\alpha = 0.77$ (t_2)) is operationalized with four items. "The usage of Facebook is easy" is an example for capturing perceived ease of use. For all items, we utilized a 7-point Likert scale.

Behavior is measured in the survey in two different ways. First, *adoption behavior* is used in order to distinguish between adopters and non-adopters. Participants are asked to indicate whether they are currently adopters or non-adopters of Facebook. Therefore, we offer the response, "Currently, I use Facebook". This is of particular interest for research discussing digital divide (e.g., Hsieh et al. 2011) as well as research identifying reasons influencing adopters and non-adopters behavior in a separate manner (e.g. Venkatesh and Brown 2001). Second, *usage behavior* is captured to determine the extent of Facebook usage and hence to depict behavior in a richer manner (Burton-Jones and Straub 2006). Therefore, it is suggested in recent research to capture the number of features of a technology, which are used. Hence, it seems highly suitable to measure the extent to which the networking platform is used. Therefore, eight purposes are identified from recent research discussing Facebook usage (e.g., Khan and Jarvenpaa 2010; Krasnova et al. 2010), which can be performed by using Facebook. Within the survey, we ask participants to indicate whether they use these features of Facebook. Among others, we ask "I use Facebook to share information with friends" (Krasnova et al. 2010) or "I use Facebook to coordinate events" (Khan and Jarvenpaa 2010). With the resulting answers, we determine the extent of features to which Facebook is used by participants. In both cases behavior is measured in the second survey, so that it reflects recent behavior, and we assigned it the period $t_{1\text{-}2}$.

Research Results

In order to examine the proposed influence of dispositional resistance, we focus on the newly developed hypotheses and investigate them by performing six regression models (one hierarchical moderated binary logistic regression analysis for the intention-behavior gap analysis and five separated moderated hierarchical regression analyses for belief updates over time). Hence, we solely examine the validity of the newly developed moderating hypotheses. Before providing these results, Table 2 contains the means, standard deviations, and inter-correlations of all variables studied in this article.

Table 2. Means, Standard Deviations, Inter-correlations among Study Variables

		Mean	SD	1	2	3	4	5	6	7	8	9	10
1	Age	39.50	13.36										
2	Gender	1.38	0.49	-0.168*									
3	Dispositional Resistance	3.73	0.90	-0.079	-0.064								
4	PU (t_1)	3.90	1.90	-0.152	0.086	-0.120							
5	PU (t_2)	3.99	1.94	-0.067	0.098	-0.079	0.749**						
6	PEOU (t_1)	3.89	1.48	-0.095	0.112	-0.065	0.773**	0.564**					
7	PEOU (t_2)	4.01	1.45	-0.024	0.086	-0.030	0.620**	0.775**	0.672**				
8	BInt (t_1)	3.90	2.38	-0.221*	0.030	-0.051	0.870**	0.758**	0.703**	0.628**			
9	BInt (t_2)	3.94	2.27	-0.041	-0.004	-0.081	0.702**	0.870**	0.543**	0.717**	0.826**		
10	Adoption Behavior (t_{1-2})	0.63	0.48	-0.126	-0.058	-0.312**	0.502**	0.673**	0.414**	0.589**	0.629**	0.691**	
11	Usage Behavior (t_{1-2})	2.67	2.84	-0.136	0.061	-0.193*	0.641**	0.715**	0.464**	0.541**	0.700**	0.742**	0.444**

*: $p < 0.10$; **: $p < 0.05$

The Moderating Influence of Dispositional Resistance on Belief Updates

In order to test the hypothesized role of dispositional resistance as a moderator within belief-update theory (Hogarth and Einhorn 1992; Bolton 1998), two separate moderated hierarchical regression analyses are performed for perceived usefulness and perceived ease of use.

For each regression analyses, the variables perceived usefulness t_1, perceived ease of use t_1, dispositional resistance, and the interaction terms are centered before entering them into the model in order to remove multicollinearity (Cohen et al. 2002). Afterwards, three steps are performed, whereby the corresponding belief – in terms of perceived usefulness or ease of use – is integrated into the model in the first step. In a second step, dispositional resistance as the moderator variable is entered into each separate model. In the last step, the interaction term is entered to each regression analyses. For individuals' belief update of perceived usefulness and perceived ease of use, results reveal a significant positive impact of the prior beliefs in t_1, a significant negative impact of dispositional resistance, and a significant positive influence of the interaction term (see Appendix). In summary, the belief update of perceived usefulness and perceived ease of use is moderated by dispositional resistance, so that resistant individuals update their beliefs less often and hence seldom change the degree of their beliefs. These results are illustrated graphically in Figure 2.

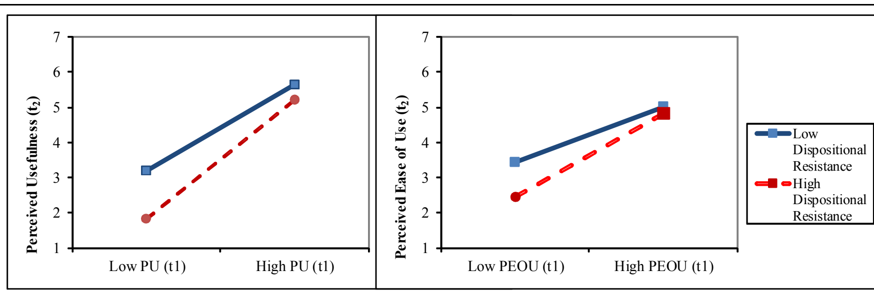

Figure 2. Moderation Effect of Dispositional Resistance on Belief Updates

The Moderating Influence of Dispositional Resistance on Self-Perceptions

Self-perception theory is used in the presented research model as underlying explanation for the influence of usage behavior (t_{1-2}) on the three perceptual beliefs perceived usefulness, perceived ease of use, and behavioral intention. In order to examine whether dispositional resistance has a moderating effect on the usage-belief relation, three separate moderated hierarchical regression analyses are performed for perceived ease of use, usefulness, and behavioral intentions in time period t_2 as dependent variable and usage behavior as independent variable.

For the moderating analyses, variables, which are entered into the model, are again centered first. Then, the three variables usage behaviors, dispositional resistance, and the interaction term are entered step by step into the model (see Appendix). For each analysis, the independent variable has a significant positive impact on the dependent variable, a significant negative influence of dispositional resistance, and a positive effect of the interaction term. For the interaction term, results reveal that dispositional resistance moderates the relation between usage behavior and both perceptual beliefs. Hence the effect of usage behavior on perceived ease of use and the influence of usage behavior on perceived usefulness is moderated by dispositional resistance significantly. In contrast, the influence of usage behavior (t_{1-2}) on behavioral intention (t_2) is not moderated significantly by the personality trait (see Appendix). Hence, user personality in terms of dispositional resistance is of importance when researching self-perceptions, because the personality trait moderates the influence of usage behavior on perceptual beliefs but not for behavioral intentions. This is illustrated in Figure 3.

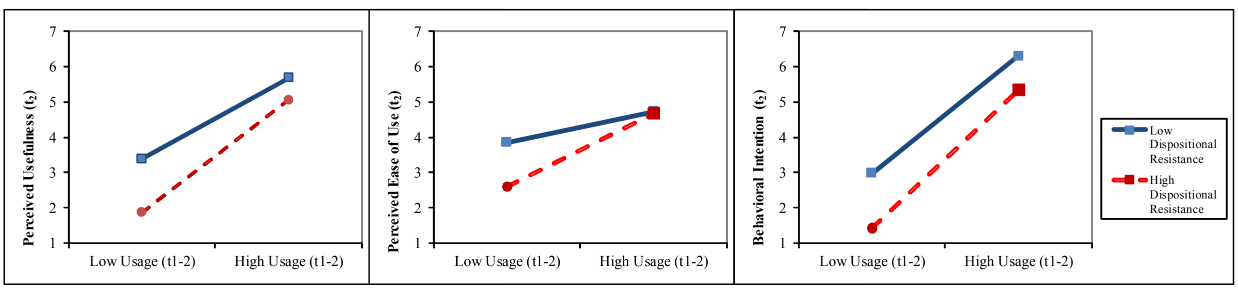

Figure 3. Moderating Effect of Dispositional Resistance on Usage-Belief Relation

The Moderating Influence of Dispositional Resistance on the Intention-Behavior Relation

In a third step, we assumed that dispositional resistance moderates the influence between behavioral intentions and adoption behavior. Based on the intention-behavior gap, we assume that less resistant individuals change their adoption status, for example from being a technology non-adopter to an adopter, while having lower behavioral intentions compared to resistant ones. Consequently, a hierarchical binary logistic regression analysis is run with adoption behavior as binary coded dependent variable. Therefore, behavioral intention, dispositional resistance, and the interaction term are centered to remove multicollinearity (Cohen et al. 2002) and afterwards entered step by step into the model (see Appendix). Starting with behavioral intention which is entered first, dispositional resistance is included in a second step, and the interaction term is entered within the third step. Results reveal that the adding of each factor enhances R^2 significantly. Behavioral intention on its own explains 45 percent of adoption behavior. After entering dispositional resistance, the explained variance increases up to 62 percent and after entering the interaction term, the R^2 increases up to 68 percent (see Appendix). To simplify the interpretation of the binary regression analysis, the logit scale is converted into a probability scale. Due to the nonlinearity of the probability scale, which is based on equation probability (adoption behavior) = $e^{\text{logit response function}} / (1+ e^{\text{logit response function}})$ (Hosmer and Lemeshow 2000), the resulting figure differs from traditional interaction plots. Thereby, the β-values listed in step 3 of the model including all variables (see Appendix) as well as selected levels of behavioral intentions and +/-0.5 standard derivations for the hypothesized moderator are used to generate Figure 4 (Flom and Strauss 2003). This figure and the results of the binary regression analysis supports Hypothesis 3 and moreover the figure displays that less resistant individuals transfer already lower intentions into behavior.

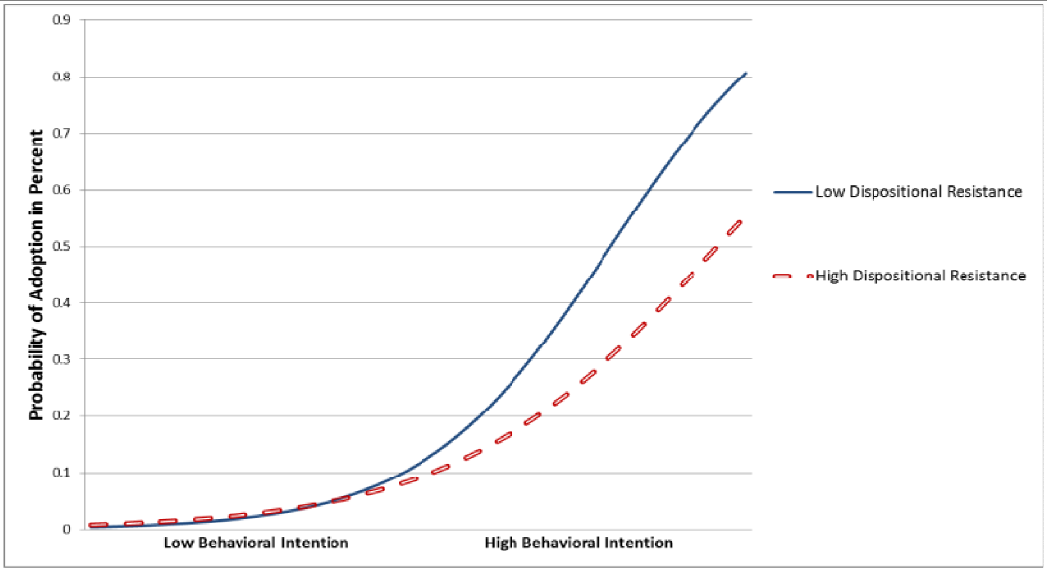

Figure 4. Plot of interaction between Behavioral Intention and Dispositional Resistance

The Strength of Effect of the Moderator Dispositional Resistance

When determining the strength of effect of moderating effects, prior research recommends using ΔR^2 or effect size (f^2) instead of referring to regression coefficients (Carte and Russell 2003). ΔR^2 indicates the variance in the dependent variable, which is explained additionally after entering the interaction term into the model and the effect size indicates the extent of the moderation effect. For each tested moderation effect, ΔR^2 as well as f^2 values are reported in Table 3. Results reveal that ΔR^2 ranges between two and six percent for the five cases in which significant effects are identified. Concerning f^2 values, results range between 0.038 and 0.188. Cohen (1988) suggests thresholds to interpret f^2 values (effect size: >.35=strong, >.15=medium,>.02=weak). Hence, the moderating effect of dispositional resistance on the relation between behavioral intentions and adoption behaviors is medium. The moderating effect on belief-updates and self-perceptions is weak for perceived usefulness and perceived ease of use.

Table 3. Strength of Effect of the moderator Dispositional Resistance

Theory / Model	Dispositional Resistance as Moderator					
	Intention-Behavior Relation (TAM)	Belief Update Theory		Self-Perception Theory		
Independent Variable	Behavioral Intention (t_1)	Perceived Usefulness (t_1)	Perceived Ease of Use (t_1)	Usage Behavior (t_{1-2})	Usage Behavior (t_{1-2})	Usage Behavior (t_{1-2})
Dependent Variable	Adoption Behavior (t_{1-2})	Perceived Usefulness (t_2)	Perceived Ease of Use (t_2)	Perceived Usefulness (t_2)	Perceived Ease of Use (t_2)	Behavioral Intention (t_2)
significant interaction term	Yes	Yes	Yes	Yes	Yes	No
R^2	68%	58%	47%	54%	37%	61%
ΔR^2	6%	3%	2%	2%	6%	0%
f^2	0.188	0.071	0.038	0.043	0.095	0.000
Cohen (1988)	medium effect	weak effect	weak effect	weak effect	weak effect	no effect
Kenny (2011)	large moderation effect	large moderation effect	large moderation effect	large moderation effect	large moderation effect	no moderation effect

Note: ΔR^2 indicates the additional variance within the independent variable that is explained after entering the interaction term into the model.
Cohen (1988) interprets effect sizes in general (> 0.35 = strong; > 0.15 = medium; > 0.02 = weak effect),
Kenny (2011) interprets effect sizes for moderators (> 0.025 = large; > 0.01 = medium; > 0.005 = small moderation effect)

Based on a 30-year review on moderating effect sizes in multiple regression analyses revealing a median observed effect size of .002 (Aguinis et al. 2005), Kenny (2011) adapts the threshold of Cohen (1988) to moderating relevant scenarios and suggests an updated classification of f^2-values for moderating effect sizes, so that Cohen's (1988) thresholds have to be relativized. Here, the threshold .005 or more for small, .01 or more for medium, and by more than .025 large moderation effects are suggested. Hence, all investigated moderation effects with a significant interaction term can be classified as large (Table 3).

Summing up, hypotheses 1, 2a, 2b, 3a, and 3b could be confirmed.

The Influence of Common Method Bias and Control Variables

Research with empirical data emphasizes the importance of considering common method bias (Podsakoff et al. 2003). While developing the questionnaire, we paid attention to each item in order to avoid using ambiguous and unfamiliar terms. Next, some items were reverse-coded and we assured participants' of their anonymity and explained in some introductory words that there is no right or wrong answer.

In order to exclude the influence of CMB on the presented results, we captured data to two different points in time. In addition, to provide a statistical indicator we perform the Harman's single factor test (Harman 1976). This test investigates whether the majority of the variance can be explained by one single factor. Here, it is often required that this value is less than 50 percent of the variance of all indicators that is explained with the single factor. Within our data, only 36.52 percent of the variance is explained with one factor. Moreover, an additional common method factor is included in each regression analysis. In order to calculate this factor, we included items, such as "*I like chocolate*", into the survey. Nonetheless, the results as well as the significance levels all remain stable after including this factor. In summary, these results suggest that no signs of common method bias are observable in our data (Podsakoff et al. 2003).

Next, we checked our results concerning some additional variables to exclude those that have an influence on our results. Due to the skewed distribution of gender, this demographic value is included, but Table 2 indicates that it has no effect on dispositional resistance, beliefs, or behavior. In addition, the effect of age is considered, but it is solely correlated with gender and behavioral intention in t_1 (Table 2). Eventually, we controlled the influence of both variables in the hierarchical regression analyses. Therefore, an additional step is considered within each analysis (see Appendix), but results show that both control variables have no significant effect on each dependent variable and R^2 values do not increase.

Discussion, Future Research, and Limitations

This research uses the trait dispositional resistance in order to examine why individuals change the degree of their beliefs over time and what prevents them from transferring intentions into behavior. Thereby, this research responds to the call by Benbasat and Barki (2007), who point out that longitudinal analysis is a promising approach for gaining further insights into technology adoption behavior.

The first research question concentrates on the updating of beliefs based on prior beliefs and usage behavior. Concerning the updating of beliefs, we base our research on IFTU and belief-update theory. We extend the underlying theory IFTU by arguing that the change in degrees of beliefs is influenced by user personality. Hence, some individuals are more consistent within their beliefs, whereas others update their beliefs more frequently and change the degree of their beliefs. As the consistency within views and beliefs depends on personality traits such as dispositional resistance (Oreg 2003), our research examines the influence of dispositional resistance on belief updates over time. Results confirm our hypotheses that resistant individuals are more consistent concerning the degree of their perceived usefulness and perceived ease of use over time than less resistant ones. These results extend current knowledge in explaining that beliefs in relation to technology are updated differently by individuals, based on their personality trait dispositional resistance.

Moreover, the effect of the personality trait dispositional resistance on the relation between usage behavior and the formation of beliefs is examined. Therefore, we base our research on self-perception theory and hence provide a contribution to this theory, which suggests that the higher the usage the better the resulting beliefs. This knowledge is extended as we verify that individuals form beliefs based on prior and current usage behavior differently. Results indicate that resistant individuals, who use a technology to a low extent, have worse beliefs regarding the usefulness and ease of use of a technology compared to less resistant individuals. Nonetheless, the perceived usefulness and perceived ease of use for individuals using technologies frequently is equally for high and less resistant individuals. In contrast to that, behavioral intentions are – independent of the extent of usage – less for resistant individuals compared to less resistant ones, so that this relation is not moderated. This finding is significant as it verifies that personality traits are central when investigating the formation of beliefs regarding technologies over time. As a consequence, we confirm that future longitudinal analyses should take account of personality in order to build on the findings in this article that some individuals update beliefs less often.

The practical relevance of changing beliefs is described in the following. Whenever an organization introduces an information system, it is important that individuals develop positive beliefs in order to use IS fully (Kim and Kankanhalli 2009; Polites and Karahanna 2012). Our results show, that the less resistant develop more positive beliefs in t_2, based on their belief in t_1 (Figure 2) and their usage behavior (Figure 3). This is different for resistant individuals with negative beliefs in t_1. Here, individuals with a low extent of technology usage do not develop positive beliefs over time in contrast to individuals using a technology frequently (Figure 2 and 3). Hence, we contribute the finding that managers can reduce the development of more negative technology-related beliefs of individuals when managers provide training courses. Due to the fact that individuals have to deal with and use the technology during these courses and hence develop more positive beliefs over time (see Figure 5). Next, results indicate that more resistant individuals change the degree of their beliefs less often. Hence, managers have to discuss with more resistant employees in particular and convince them to use the technology and promote its advantages.

Our results regarding changing beliefs based on dispositional resistance and usage behavior over time is illustrated in Figure 5. On the left side, Figure 5 illustrates that individuals with positive beliefs in t_1 have more positive beliefs in t_2 independent of their dispositional resistance. Hence, they keep their positive outlook independently of the surrounding conversations and information. However, Figure 5 also indicates that those individuals with rather negative beliefs in t_1 change their beliefs into rather positive ones when they are less resistant. Consequently, these individuals can be convinced by the usefulness or ease of use of a technology solely based on the surrounding information. Nonetheless, resistant individuals retain their negative beliefs to the extent that further interventions might be necessary to update their beliefs in a positive manner. In this context, the right side of Figure 5 illustrates that the usage behavior might be a factor in order to change negative beliefs into positive ones, because all individuals, independent of their dispositional resistance, have more positive beliefs when using a technology frequently. Hence, also those individuals with rather negative beliefs in t_1, who are high in dispositional resistance, develop rather positive beliefs based on high usage behavior. However, when using a technology less often resistant individuals maintain their negative beliefs. When combining this knowledge, which is illustrated in two distinct pictures in Figure 5, we can state that solely resistant individuals, who seldom use a technology, maintain their negative beliefs over time.

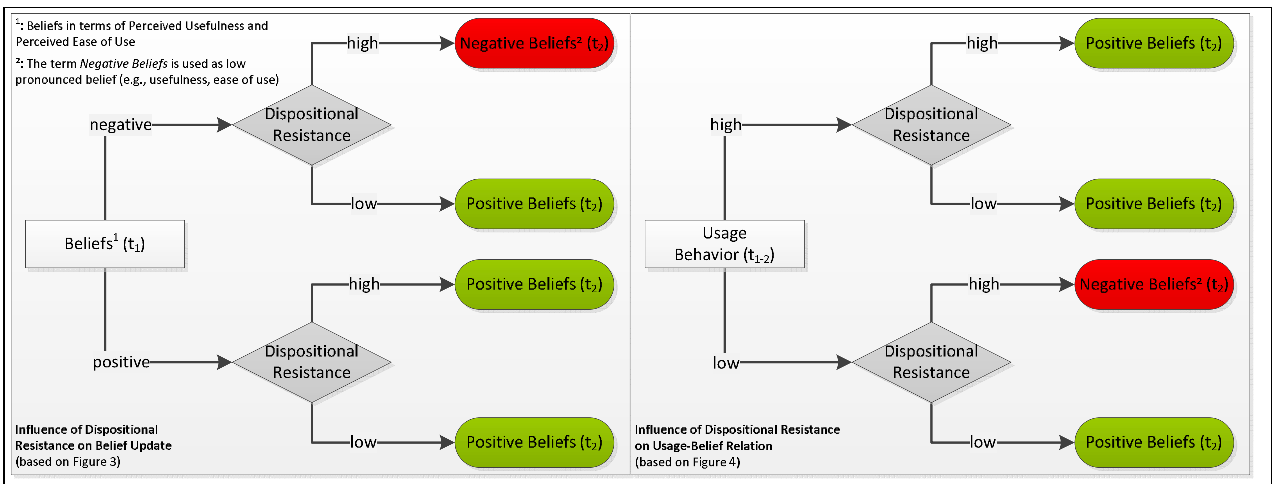

Figure 5. Belief Changes over time based on Dispositional Resistance and Usage Behavior

The second research question concentrates on the influence of personality on the intention-behavior gap (Bhattacherjee and Sanford 2009). This gap results from inconsistencies between intentions and behavior as only a small number of individuals with high intentions actually change their behavior. Motivated by recent research suggesting that personality traits moderate the intention-behavior relation (Ajzen 2002a, Allen et al. 2005), our research applies the trait dispositional resistance to close the gap. The underlying hypothesis assumes that less resistant individuals transfer lower intentions into behavior than resistant individuals. The results of a data set of participants with steady and changing adoption behavior confirms our hypothesis and identifies dispositional resistance as a moderator of the intention-behavior relation. In more detail, 45 percent of future behavior is explicable through intention alone, but when considering additional dispositional resistance as a moderator, 68 percent of future behavior can be explained. This indicates that resistant individuals change their behavior less often or at least at a later time, even though they have strong intentions. This extends current knowledge on two significant points. Frist of all, we validate that personality traits are not solely moderators of belief-intention relations as suggested by Devaraj et al. (2008), but it also moderates the intention-behavior relation when focusing on two different points in time. Second, Bhattacherjee and Sanford (2009) suggest attitude strength in terms of personal relevance and related expertise as a moderator of the intention-usage relation to close the intention-behavior gap. We hypothesize and validate that next to attitudes, personality traits represent a possibility for closing this gap. Compared to the model of Bhattacherjee and Sanford (2009), which explain 73.2 percent of behavior with two moderators and two dependent variables, we explain a comparable amount of variance (68 percent) with one moderator and one dependent variable. Hence, we contribute to technology adoption research by finding that user personality in general and dispositional resistance in detail is essential when understanding intention-behavior gap or digital divide, because resistant individuals are not only less willing to change their status quo, but have to develop higher behavioral intentions before adopting a technology (Figure 4).

In addition to that, we extend current knowledge of the influence of personality traits on IT-related beliefs over time. Up to now, research articles investigating the impact of personality traits in IS research capture data at only one point in time. Among others, Devaraj et al. (2008) investigate the effect of traits on perceived usefulness, subjective norm, and as a mediator of the usefulness-intention or subjective norm-intention relation. Besides, McElroy et al. (2007) concentrate on examining the influence of personality traits on behaviors. Hence, we extend this knowledge by using longitudinal data and examining the influence of the trait of dispositional resistance as a moderator (see Figure 6). As a consequence, we can combine these aspects and determine that traits have a direct effect on beliefs (Devaraj et al. 2008) and a moderating one on belief updates.

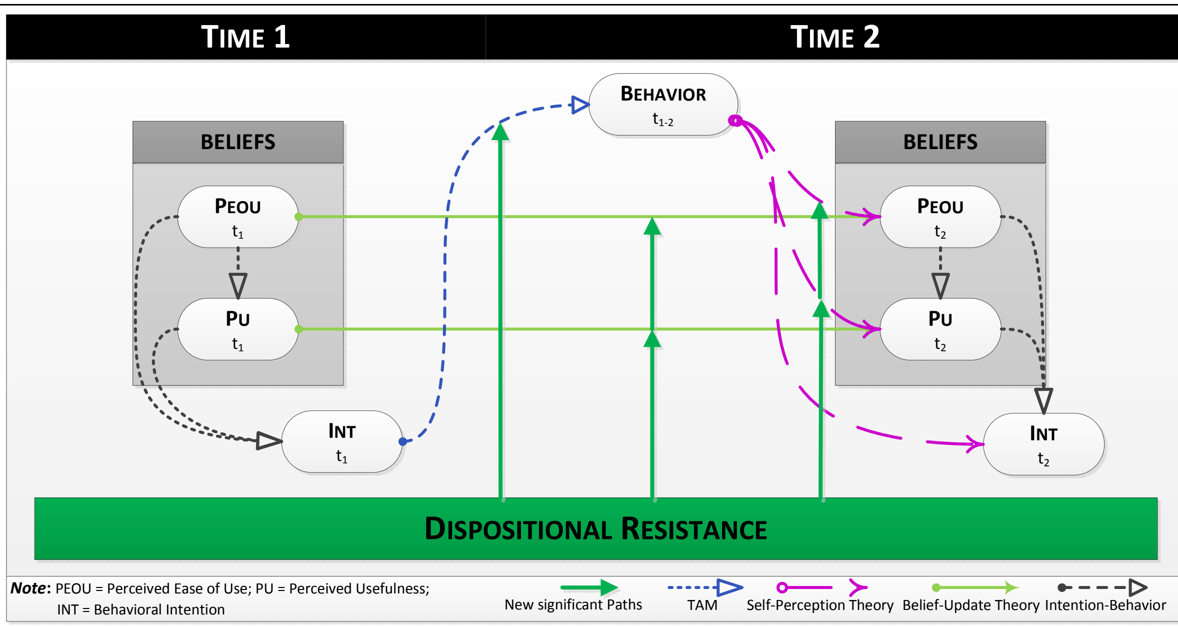

Figure 6. Summary of Research Results

Eventually, we provide a contribution for research into user resistance. Although prior research has discussed user resistance as a certain type of behavior (Kim and Kankanhalli 2009; Klaus et al. 2010) or as a perceptual belief (Bhattacherjee and Hikmet 2007), it has not been investigated from the perspective of personality traits. Here, we contribute the finding that resistance in terms of a personality trait also influences whether or not a technology is adopted by individuals. Hence we state that user resistance is a multi-faceted phenomenon, which has to be investigated from different perspectives in terms of behavior, perceptual beliefs, and personality traits in order to understand user resistance as a whole.

Future Research

Based on these results, future research might investigate the influence of other individual differences, such as age, gender, experience, or other personality traits, such as optimism, on changing beliefs in order to determine whether these individual differences also have a significant impact. Moreover, an experimental setting might be useful in order to determine the time-span after which resistant individuals transfer high behavioral intentions into adoption behavior compared to less resistant individuals. In addition, as this research examines how beliefs become more positive over time based on personality and usage behavior, future research might investigate whether particular situations exist in which positive beliefs become negative. This could, for example, be investigated in organizational settings when an efficient IS is changed and causes problems. Here the influence of dispositional resistance on belief updates might be interesting to observe because recent research identifies that negative and positive events are processed differently (Ito et al. 1998). In addition to that, future research might break up the overall construct of dispositional resistance and concentrate on the four dimensions separately in order to establish which dimension has the highest impact.

Limitations

While intending to examine the impact of personality on belief updates as well as the intention-behavior gap, this research concentrates on one particular trait. This is carried out due to the point described above as our research objective of changing beliefs fit the objectives for which Oreg (2003) develops the scale of dispositional resistance. In addition, psychology has discussed whether research focusing on personality should use one particular trait that fits the research objective or whether higher-order concepts, such as the Big Five (Zuckerman et al. 1993), should be used. Here, the consensus opinion of this research is that particular traits should be used whenever one can be identified that fits the research objective, because these have a higher explanatory power in different fields of application (Paunonen and Nicol 2001; Lounsbury et al. 2002). Nevertheless, future research has to extend the findings of this article by examining other traits, demographics, or self-perceptions. Another limitation of the approach used here is that we focus on only one particular technology. Here, we concentrate on Facebook and voluntary technology settings. In addition, we cannot determine why individuals update their beliefs. This cannot be identified using our empirical studies and so future research might address this limitation by performing an experiment or qualitative approaches to identify the specific triggering event of a belief update. Besides, as table 2 illustrates there is neither a significant correlation between dispositional resistance and perceived usefulness nor between dispositional resistance and perceived ease of use. However, prior research has identified significant correlations (Nov and Ye 2008; Maier et al. 2011), so that future research has to examine whether these relations are solely significant in mandated technology usage settings. Next, we used Likert scales within our measures instead of semantic differentials. As a consequence, we cannot give any assurance as to whether or not participants expressing disagreement at items concerning usefulness and ease of use in our survey intend to express whether they perceive the usage of OSNs as useless and difficult to use or are just indicating low levels of usefulness and ease of use. Eventually, the presented model does not include the social context. By discussing subjective norm as an antecedent of behavioral intentions as suggested by the Theory of Planned Behavior (Ajzen 1991), results might differ.

Conclusion

The results of this research show that individuals change their beliefs differently based on their personality. Therefore, the personality trait dispositional resistance is discussed as a moderator within IFTU (Kim and Malhotra 2005). Hence, IFTU is extended by non-linear effects. Based on the significant moderation effects (see Figure 6), future research should include moderators in articles discussing dynamic interplays between beliefs, behavioral intentions, and behavior. Next to this, personality in terms of dispositional resistance is verified as an essential factor whether individuals transfer behavioral intentions into adoption behavior or not. Consequently, future articles intending to explain adoption behavior based on intention-based models should integrate traits, because every individual has an individually threshold when behavioral intentions are transferred into forms of adoption behavior.

Consequently, we contribute to research discussing technology usage and adoption research by responding to the call of Benbasat and Barki (2007) to investigate beliefs and behavior using longitudinal analyses. Based on the results, which highlight the importance of user personality, we furthermore extend the call by suggesting that longitudinal research should include personality traits, in order to take into account the fact that some individuals change the degrees of their beliefs less often.

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Appendix

Table 4. Hierarchical regression analysis of the influence of dispositional resistance on belief updates

Dependent Variable	Variable	Step 1				Step 2				Step 3				Step Control			
		B	β	95% lower	95% upper	B	β	95% lower	95% upper	B	β	95% lower	95% upper	B	β	95% lower	95% upper
Perceived Usefulness (t_2)	Constant	4.00		3.76	4.25	4.00		3.76	4.24	3.97		3.73	4.21	3.71		2.59	4.82
	PU (t_1)	1.394	0.726**	1.148	1.640	1.437	0.748**	1.196	1.678	1.452	0.756**	1.213	1.690	1.450	0.761**	1.220	1.704
	DRes					-0.339	-0.175**	-0.582	-0.095	-0.448	-0.232**	-0.712	-0.185	-0.440	-0.228**	-0.708	-0.174
	DRes x PU (t_1)									0.235	0.136**	0.010	0.469	0.231	0.134**	-0.007	0.459
	Gender													0.031	0.008	-0.484	0.546
	Age													0.006	0.039	-0.012	0.024
	R^2 (ΔR^2)	0.52				0.55 (0.03)				0.58 (0.03)				0.58 (0.00)			
	Δf (*df*)	125.96 (1)**				7.61 (1)**				3.95 (1)**				0.18 (2)^{NS}			
Perceived Ease of Use (t_2)	Constant	3.97		3.76	4.18	3.97		3.76	4.17	3.93		3.73	4.14	3.83		2.90	4.76
	PEOU (t_1)	0.957	0.658**	0.750	1.164	0.999	0.681**	0.783	1.198	0.980	0.676**	0.775	1.186	0.979	0.673**	0.769	1.190
	DRes					-0.198	-0.138**	-0.402	0.007	-0.294	-0.205**	-0.520	-0.069	-0.291	-0.203**	-0.521	-0.062
	Gender									0.201	0.151**	-0.060	0.409	0.200	0.151**	-0.013	0.413
	Age													0.039	0.013	-0.395	0.473
	DRes x PEOU (t_1)													0.001	0.011	-0.014	0.017
	R^2 (ΔR^2)	0.43				0.45 (0.02)				0.47 (0.02)				0.47 (0.00)			
	Δf (*df*)	83.83 (1)**				3.668 (1)*				3.71 (1)*				0.02 (2)^{NS}			

Note: PU = Perceived Usefulness; PEOU = Perceived Ease of Use; DRes = Dispositional Resistance *: $p < 0.10$; **: $p < 0.05$

Table 5. Hierarchical regression analysis of the influence of dispositional resistance on self-perception theory

Dependent Variable	Variable	Step 1				Step 2				Step 3				Step Control			
		B	β	95% lower	95% upper	B	β	95% lower	95% upper	B	β	95% lower	95% upper	B	β	95% lower	95% upper
Perceived Ease of Use (t_2)	Constant	4.02		3.809	4.231	4.03		3.823	4.243	3.96		3.753	4.170	3.40		2.450	4.360
	USE (t_{1-2})	0.788	0.549**	0.574	1.002	0.841	0.586**	0.620	1.062	0.734	0.512**	0.510	0.959	0.734	0.512**	0.505	0.964
	DRes					-0.187	-0.134**	-0.402	0.028	-0.326	-0.234**	-0.553	-0.100	-0.315	-0.226**	-0.543	-0.087
	DRes x USE (t_{1-2})									0.298	0.262**	0.105	0.491	0.299	0.263**	0.105	0.494
	Gender													0.213	0.073	-0.220	0.647
	Age													0.007	0.064	-0.009	0.022
	R^2 (ΔR^2)	0.30				0.31 (0.01)				0.37 (0.06)				0.37 (0.00)			
	Δf (*df*)	53.115 (1)**				2.977 (1)*				9.322 (1)**				0.705 (2)^{NS}			
Perceived Usefulness (t_2)	Constant	4.03		3.784	4.270	4.06		3.824	4.290	4.00		3.767	4.239	3.52		2.439	4.604
	USE (t_{1-2})	1.330	0.691**	1.084	1.576	1.451	0.754**	1.206	1.696	1.371	0.712**	1.116	1.625	1.369	0.711**	1.108	1.629
	DRes					-0.430	-0.228**	-0.670	-0.190	-0.535	-0.284**	-0.793	-0.276	-0.525	-0.279**	-0.786	-0.265
	DRes x USE (t_{1-2})									0.225	0.146**	0.004	0.445	0.227	0.147**	0.005	0.449
	Gender													0.204	0.052	-0.286	0.693
	Age													0.005	0.036	-0.012	0.023
	R^2 (ΔR^2)	0.47				0.52 (0.05)				0.54 (0.02)				0.54 (0.00)			
	Δf (*df*)	114.285 (1)**				12.579 (1)**				4.071 (1)*				0.429 (2)^{NS}			
Behavioral Intention (t_2)	Constant	4.01		3.736	4.276	4.05		3.797	4.304	4.01		3.752	4.273	4.01		2.816	5.210
	USE (t_{1-2})	1.700	0.739**	1.423	1.977	1.865	0.811**	1.595	2.135	1.808	0.786**	1.523	2.093	1.817	0.790**	1.526	2.108
	DRes					-0.560	-0.253**	-0.819	-0.301	-0.629	-0.285**	-0.911	-0.347	-0.630	-0.285**	-0.915	-0.345
	DRes x USE (t_{1-2})									0.150	0.083^{NS}	-0.091	0.392	0.148	0.082^{NS}	-0.096	0.392
	Gender													-0.064	-0.014	-0.604	0.477
	Age													0.002	0.013	-0.017	0.021
	R^2 (ΔR^2)	0.54				0.61 (0.06)				0.61 (0.00)				0.61 (0.00)			
	Δf (*df*)	147.972 (1)**				18.273 (1)**				1.518 (1)^{NS}				0.066 (2)^{NS}			

Note: USE = Usage Behavior; DRes = Dispositional Resistance *: $p < 0.10$; **: $p < 0.05$

Table 6. Hierarchical linear regression analysis of the influence of dispositional resistance on the intention-behavior relation

Dependent Variable	Variable	Step 1				Step 2				Step 3				Step Control			
		β	Exp(β)	95% lower	95% upper	β	Exp(β)	95% lower	95% upper	β	Exp(β)	95% lower	95% upper	β	Exp(β)	95% lower	95% upper
Adoption Behavior (t_{1-2})	Constant	1.25	3.50**			1.79	5.97**			3.11	22.45**			3.82	45.72**		
	BInt (t_1)	1.710	5.550**	2.99	10.30	2.470	11.826**	4.76	29.38	3.627	37.594**	7.46	189.37	3.678	39.578**	7.35	213.05
	DRes					-1.719	0.179**	0.08	0.41	-1.934	0.145**	0.06	0.38	-1.988	0.137**	0.05	0.37
	DRes x BInt (t_1)									-1.147	0.317**	0.14	0.71	-1.158	0.314**	0.14	0.73
	Gender													0.087	1.091	0.33	3.56
	Age													-0.019	0.981	0.94	1.03
	R^2 (ΔR^2)	0.45				0.62 (0.17)				0.68 (0.06)				0.68 (0.00)			
	Δf (*df*)	48.337 (1)**				24.146 (1)**				9.447 (1)**				0.804 (2)^{NS}			

Note: Bint = Behavioral Intention; DRes = Dispositional Resistance   *: p < 0.10; **: p < 0.05