Generalizations on consumer innovation adoption:

A meta-analysis on drivers of intention and behavior

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Abstract

Previous research has shown that consumer intentions to adopt innovations are often poor predictors of adoption behavior. An important reason for this may be that the evaluative criteria consumers use in both stages of the adoption process weigh differently. Using construal level theory, we develop expectations on the influence of innovation characteristics across the intention and behavior stages of the adoption process. Using meta-analysis, we derive generalizations on drivers of intentions and actual innovation adoption behavior. The results show important differences across both stages. Consumers show higher levels of adoption intention for innovations that are more complex, better match their needs, and involve lower uncertainty. However, consumers are found to actually adopt innovations with less complexity and higher relative advantages. Adopter demographics are found to explain little variance in adoption intention and behavior, whereas adopter psychographics are found to be influential in both stages. These findings have implications for innovation adoption theory, for managers involved in new product and service marketing, and for future research on innovation adoption.

Key terms: *Innovation adoption, intention versus behavior, meta-analysis.*

1. Introduction

Understanding whether and why consumers will adopt a new product or service is a critical insight for managers involved in marketing innovations. It is common practice to obtain such an understanding based on market research of consumers' attitudes toward the innovation and their purchase intention. However, many marketers have found out the hard way that consumers who "talk the talk" in surveys do not always "walk the walk" when it comes to innovation adoption. Consider for example the videophone. As early as 1964, AT&T tested its version of this innovation, the *Picturephone*, during the New York World Fair (Schnaars and Wymbs 2004). Market researchers interviewed almost 700 individuals making transcontinental videophone calls. Respondents rated the service favorably, and 45% indicated a need for the service at home. However, the launch of the innovation in the consumer market failed, as few consumers adopted the innovation. After a later unsuccessful launch in the business market, AT&T eventually decided to terminate the *Picturephone* by the mid-1970s. The case of the videophone can hardly be considered an isolated example. A recent report by Synovate that reviewed studies on product purchase intention and behavior from diverse categories, such as fast-moving consumer goods, cars, PCs, appliances, clothing, and home furnishings, suggested that "91% of the variance [in purchase behavior] is not captured by purchase intent" (Synovate 2007, p. 4).

Managerial practice shows that intentions are often used as proxy measures for adoption behavior (Van Ittersum and Feinberg 2010; Young, DeSarbo and Morwitz 1998). The case of the videophone painfully illustrates that market research showing favorable evaluation and high adoption intention of an innovation can be misleading. Indeed, academic research on the adoption of innovations has shown that intentions are far from perfect predictors of behavior. A meta-analysis by Sheppard, Hartwick and Warshaw (1988) reported a correlation of .53 between intention and behavior. Moreover, Morwitz, Steckel and Gupta (2007) found that the correlation between intention and behavior was significantly lower for new products than for existing ones.

Several reasons have been suggested for this gap (e.g., Morwitz et al. 2007; Sun and Morwitz 2010; Van Ittersum and Feinberg 2010), including consumers' change of intentions over time (Morrison 1979), the use of biased estimates in research (Van Ittersum and Feinberg 2010), and the inability of the consumer to anticipate unexpected events that may affect the adoption decision (Morwitz et al. 2007).

Typically, the evaluation of a product or service, such as an innovation, is a goal-directed process in which consumers evaluate its attributes with certain use purposes and situations in mind (e.g., Gardial, Clemons, Woodruff, Schumann, and Burns 1994; Vandecasteele and Geuens 2010). Innovation adoption is best represented by a process of multiple stages through which an individual passes, from first awareness to continued use of the innovation (Rogers 2003). During this complex decision process, the potential adopter forms perceptions of the characteristics of the innovation (e.g., Castaño, Sujan, Kacker, and Sujan 2008; Wood and Lynch 2002) and weighs them in a choice decision (e.g., Bettman 1979). At different stages of the innovation adoption process, use purposes and situations may be perceived differently, thus affecting the weight of evaluative criteria in the decision process. Consumers may therefore weigh attributes differently in situations of purchase intention versus purchase behavior, resulting in an imperfect relationship between intention and behavior (Gollwitzer 1999). For example, in the case of the videophone, the high quality of personal visual communication may have led consumers to a favorable pre-adoption evaluation of the innovation, indicating high adoption intentions, whereas the importance of its perceived costs may have prevented consumers from actual purchase. Thus, it is best to distinguish intention and behavior as distinct dependent variables (Bemmaor 1995; Jamieson and Bass 1989) that represent different, subsequent stages of the innovation adoption process (Rogers 2003).

A rich body of research has developed in the past decades that addresses factors affecting innovation adoption decisions by consumers in marketing science (Hauser, Tellis, and Griffin 2006; Rogers 2003). However, only more recently have insights into how antecedents of consumer innovation adoption differ between adoption process stages been developed in the literature (e.g., Alexander, Lynch, and Wang 2008; Castaño et al. 2008; Wood and Moreau 2006). Practitioners could substantially benefit from a better understanding of the antecedents of consumers' intentions to adopt an innovation versus those of their actual behavior. Although Tornatzky and Klein (1982) have previously provided insight on innovation adoption drivers based on a meta-analysis of academic research, their study did not discriminate between intention and behavior. Moreover, their study was conducted almost three decades ago, thus excluding a large body of research conducted since then. The objective of this paper is therefore to shed more light on whether and, if so, how drivers of innovation adoption that have been considered as indicators of innovation acceptance in the literature vary across the intention and behavior stages of the adoption process. To do so, this study uses meta-analysis (e.g., Assmus, Farley, and Lehmann 1984) on antecedents of both adoption intention and adoption behavior. As such, this study aims to obtain more insight in a field of research (i.e., consumer innovation adoption) rather than in a specific relation. This meta-analysis focuses on studies in marketing literature that address the adoption of new products by consumers. We further assess whether and how contextual and methodological factors have moderated the effects found on innovation adoption. We generalize the findings of 77 studies related to consumer innovation adoption published in marketing from 1970 to mid-2007. This method allows us to obtain generalized findings on both adoption outcomes and their antecedents. The main results of this analysis include the following:

- Innovation characteristics have a strong but different effect on adoption process stages:
    - Benefits affect both intention and behavior, with compatibility being a stronger driver of intention and relative advantage of behavior;
    - Complexity has a positive effect on intention, but negatively affects adoption behavior;

    - Perceived uncertainty shows a stronger effect on intention than on adoption behavior.
- Adopter demographics show minor influence on innovation adoption.
- Adopter psychographics are found to be powerful drivers of innovation adoption, with respect to both intention and behavior.

This study contributes to the literature by showing that drivers of innovation adoption to a large extent affect intention and behavior differently. Therefore, the findings show that it is important to take a dynamic perspective of innovation adoption. The study also suggests new directions for future research and provides implications for managers involved in new product and service marketing.

This paper is organized as follows. First, we provide the theoretical background of the study. Second, we discuss the procedures that were used to conduct the literature review and the development of the database and elaborate on the methods employed to analyze the data. Third, we present the findings of the meta-analysis pertaining both to the substantive information on the effects and the existence of contextual and methodological moderators. Fourth, we discuss the findings and draw implications for practitioners dealing with the marketing of new products. Finally, we discuss the limitations of the present study and implications for future research on innovation adoption.

2. Theoretical background

2.1 Antecedents of innovation adoption

In the literature, different theoretical models have been used to explain consumer innovation adoption. Typically, studies build upon Rogers' (2003) innovation diffusion theory, the Technology Acceptance Model (Davis 1989), the Theory of Reasoned Action (Fishbein and Ajzen 1975) or the Theory of Planned Behavior (Ajzen 1985). Innovation adoption can be defined as the consumer's decision to make full use of an innovation (Rogers 2003). Although this definition implies the consumer's purchase behavior, both purchase intentions and actual purchase behavior have been used interchangeably to reflect adoption (Jamieson and Bass 1989). We explicitly distinguish between 'adoption intention' and 'adoption behavior' to reflect different explained variables, and we refer to 'innovation adoption' to reflect both concepts. Adoption intention refers to a consumer's expressed desire to purchase a new product in the near future. It relates to the consumer's state of mind before actual purchase behavior has occurred and is based on the information and perceptions the consumer has at that time. Adoption behavior, on the other hand, refers to the (trial) purchase of an innovation (Rogers 2003). Studies on adoption behavior typically analyze the perceptions and characteristics of consumers who have already purchased the innovation relative to those who have not. The latter may include non-adopters who either have a high or low intention to adopt or non-adopters who even lack awareness of the innovation.

In the innovation adoption literature, characteristics of the (potential) adopter and perceived characteristics of the innovation are found to be major drivers of innovation adoption (Gatignon and Robertson 1985; Meuter, Bitner, Ostrom, and Brown 2005; Rogers 2003; Tornatzky and Klein 1982). The number of different variables used to capture adopter characteristics is particularly large, as a lot of research has been devoted to finding traits of consumers that are likely to adopt an innovation. Adopter characteristics capture the personal traits that describe the (potential) adopter of an innovation, which can be divided into socio-demographics and psychographics. A wide range of socio-demographic characteristics has been used in research (Gatignon and Robertson 1985; Rogers 2003; Tornatzky and Klein 1982). Many studies particularly focus on consumers' age, level of education and income. Other variables that are considered frequently include household size, gender, and family life cycle. Adopter psychographics including innovativeness, opinion leadership, media proneness, and involvement are among the variables most frequently used to explain adoption. Less frequently used variables include, for example, price consciousness, brand familiarity, self-confidence, and dogmatism. Innovation characteristics refer to the attributes consumers use to evaluate an innovation. In the innovation adoption literature, these are generally represented by the consumer's perception of the relative advantage, compatibility, complexity, trialability, observability (Rogers 2003), and uncertainty or risk (Hoeffler 2003; Ostlund 1974) of the innovation. Table 1 provides definitions and the expected effects of the innovation characteristics. Table 2 provides definitions and the expected effects of adopter characteristics that have been related most frequently to innovation adoption in the literature.

[Insert Tables 1 and 2 here]

2.2 The influence of innovation characteristics on intention and behavior

Innovation adoption studies typically do not distinguish between the effect of innovation characteristics on intention and behavior, despite empirical evidence that consumers employ different evaluative criteria in alternative stages of their decision-making process (e.g., Gardial et al. 1994; Karahanna, Straub, and Chervany 1999; Mittal, Kumar, and Tsiros 1999; Wilton and Pessemier 1981). More recent studies, however, acknowledge the importance of dynamic effects of evaluative criteria in the innovation adoption process and find support for the notion that these do affect subsequent process stages differently (Alexander et al. 2008; Castaño et al. 2008; Wood and Moreau 2006). Some of this work builds on temporal construal theory (Trope and Liberman 2003), which provides guidance as to how innovation characteristics may affect temporally distinct decisions. We build on this work to formulate expectations about how the intention and behavior stages of the innovation adoption process, which generally reflect distinct points in time, may be affected by perceived innovation characteristics.

The basic premise of temporal construal theory (or construal level theory [CLT], e.g., Trope and Liberman 2003) is that individuals weigh evaluative criteria (e.g., product attributes) related to a future behavior (e.g., product purchase) differently, depending on whether the behavior is closer or further away in time. Behaviors that are more distant in time, such as reflected by innovation adoption intentions, are more likely to be affected by relatively abstract or general considerations. Behaviors that are close in time, as reflected by adoption behavior, are more likely to be affected by concrete, specific, and context-dependent considerations. This distinction is especially important for understanding how perceived innovation characteristics may affect the intention and behavior stages of the adoption process, as it suggests a different role for the innovation's benefits versus its costs.

Benefits. According to CLT, when intending to purchase an innovation, individuals form more abstract (or higher level) representations (construals) of the focal behavior (i.e., innovation purchase). In terms of innovation adoption as a goal-directed process, these relate to superordinate goals that represent the relatively abstract "why" aspects of an action (Trope and Liberman 2003; Vallacher and Wegner 1987). The "why" aspects reflect the desirability of the behavior. In the innovation adoption process, the desirability to adopt a new product or service is higher in the case where the potential adopter perceives the innovation to be advantageous and compatible with their needs. Relative advantage reflects the benefits of the innovation over alternative offerings, providing the potential adopter with insight in its desirability. Compatibility reflects the degree to which the innovation matches the potential adopter's needs and values and is therefore an important aspect of the innovation's desirability to the individual. Based on CLT, benefits in terms of an innovation's perceived relative advantage and compatibility are expected to be weighed higher by potential adopters as they are further from actual adoption behavior (i.e., in the intention stage).

Trialability and observability do not represent benefits per se but may enable the potential adopter to more effectively assess the benefits of the innovation. Observability may help to show positive output that increases the adopter's motivation to receive the innovation's rewards (Meuter et al. 2005). Such higher desirability is likely to stimulate the consumer's intention to adopt the innovation. Trialability enables the consumer to see how the innovation works. As such, it helps the potential adopter to assess the extent of behavioral change required when adopting the innovation. In this respect, Meuter et al. (2005) found that trialability enhances consumer readiness, such that it helps the potential adopter to understand their role and to have confidence in their abilities using the innovation. Thus, trialability may especially affect the consumer's feasibility of using the innovation. As we discuss next, the latter is most relevant at the behavior stage of the adoption process. We therefore expect observability to have a stronger effect at the intention stage and trialability to have a stronger effect at the behavior stage.

Costs. CLT suggests that, as individuals approach the actual behavior, more concrete (lower level) considerations are expected to affect their actions. Instead of superordinate goals that reflect actions more distant from the actual behavior (as in the case of adoption intention), subordinate goals become more important at the behavior stage. These relate to the "how" details of the behavior (Vallacher and Wegner 1987) and, as such, reflect relatively concrete, context specific, low-level considerations (Trope and Liberman 2003). At this stage, the individual becomes more concerned with the feasibility of the behavior (Lynch and Zauberman 2006; Vallacher and Wegner 1987). The focus of the individual shifts more toward the costs involved in the behavior (Trope and Liberman 2003). This notion is consistent with loss aversion theory, which posits that individuals will focus more on potential losses than on gains when faced with a decision of behavioral change (Kahneman and Tversky 1979). At the behavior stage, individuals are therefore expected to weigh lower level, "how"-related considerations more strongly. With respect to innovation adoption, this includes the ease of use of the new product or service (i.e., its complexity). The more an innovation is perceived as complex, the more learning costs to adopt new behaviors will be involved (Hoeffler 2003; Wood and Moreau 2006). These perceived costs are likely to especially weigh heavily at the behavior stage, as the need for specific behavior changes to successfully adopt the innovation becomes apparent. The more complex the innovation and thus the higher its perceived costs, the less feasible behavior change becomes, inhibiting consumers to follow through on adoption intention with actual behavior (Alexander et al. 2008). These costs are more likely to have less weight at the intention stage (Trope and Liberman 2003), and complexity, therefore, is expected to have a less negative effect on adoption intention.

The feasibility of adoption also depends upon the perceived uncertainty (or risk) related to innovation adoption (Ostlund 1974). However, as Castaño et al. (2008) showed, uncertainty affects distant-future adoption decisions (reflected by intention) and near-future adoption decisions (reflected by behavior) differently. In the event that adoption is more distant (i.e., at the intention stage), uncertainties about benefits are more important, whereas when behavioral change is eminent (near future), consumers focus more on cost uncertainties associated with switching to the innovation and learning the new behavior (Castaño et al. 2008). Uncertainty may thus affect both intention and behavior, although in different ways.

Table 1 summarizes the expected influence of the perceived innovation characteristics in the intention and behavior stages of the adoption process. We next describe the procedure used to collect the data for the study.

3. Data

Data collection. A literature search was executed toward empirical studies published since 1970 that addressed any of the stages of the innovation adoption process and related topics. As part of this work, we carried out a series of search strategies. First, a computerized bibliographic search was performed using ABI/INFORM, ScienceDirect, Econlit, and Kluwer Online. We focused on keywords such as 'adoption', 'intention', and 'innovation'. Second, an issue-by-issue search was done of the *International Journal of Research in Marketing*, *Journal of the Academy of Marketing Science*, *Journal of Business Research*, *Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, *Journal of Product Innovation Management*, *Journal of Retailing, Management Science, Marketing Science, Proceedings of the American Marketing Association*, and *Proceedings of the European Marketing Academy Conference*. Third, we scanned the World Wide Web for working papers. Fourth, we posted a request for papers on the ELMAR mailing list. Finally, we examined the references in the publications that were obtained to find additional empirical research. The decision to include an observation in our database was based on three criteria. First, we included only studies reporting new empirical findings. Second, we restricted our analysis to consumers. We did not include studies on organizational adoption or studies on adoption of innovations by employees for business use. Third, all studies were published in the period of 1970 to mid-2007. In total, we identified 92 studies. Due to insufficient information, 15 studies could not be incorporated, resulting in 77 studies that were usable for data analysis. On average, 2.6 papers on consumer innovation adoption were published per year. The number of relations that these studies reported ranged from 1 to 191. The sample size that was used ranged from 60 to 3,687 respondents. Over 60% of the studies focused on analyzing a single innovation. Only 10% of the studies examined more than 5 innovations.

Coding. Over 200 different variables were identified that have been used to explain consumer adoption intention and/or adoption behavior. We coded all variables based on a standardized scheme to capture the reported relations. Coding was executed by two independent coders. Over 90% of the bivariate relationships were coded the same by both coders. Any remaining issues were resolved *via* discussion by the coders and researchers. A study was coded as *adoption intention* when the dependent variable was operationalized by asking respondents to rate their intention to purchase an innovation in the future. A study was coded as *adoption behavior* when the dependent variable was operationalized as a purchase of the innovation. In a few cases, the term innovativeness was used to refer to innovation adoption (e.g., Darden and Reynolds 1974; Summers 1971). If so, we re-coded the study to reflect the appropriate stage of the adoption process (intention or behavior). Innovativeness in terms of consumers' propensity to adopt new products (Hirschman 1980) was coded as a psychographic variable. In the coding procedure, several constructs were identified that were defined similarly in the literature but were represented by different names. For example, the innovation characteristic of perceived complexity, as defined by Rogers (2003), was represented in the Technology Acceptance Model (Davis 1989) as ease of use; also, perceived uncertainty and perceived risk (Ostlund 1974) were both used in previous research. We therefore developed a single definition for each construct (see Tables 1 and 2) and coded each variable accordingly.

Analysis. In total, 777 measures on 37 bivariate relations (between the dependent variables [intention/behavior] and the independent variables [innovation characteristics, adopter socio-demographics, and adopter psychographics]) were included in the meta-analysis. This is a satisfactory result and is comparable to other meta-analyses in marketing (e.g., Geyskens, Steenkamp, and Kumar 1998; Henard and Szymanski 2001). For the analysis, we selected all drivers for which more than 10 relations (for both dependent variables together) were found. This cutoff point is similar to those used by other meta-analyses (e.g., Henard and Szymanski 2001).

The strength of the bivariate relationships between intention or behavior and their antecedents has typically been reported by means of correlation coefficients. Therefore, correlations are used as measures of effect size in the meta-analysis, as previously done by other meta-analyses in marketing (Geyskens et al. 1998; Henard and Szymanski 2001). If a correlation coefficient between two variables was not reported, other statistical information, such as t-tests, F-tests, and chi-squared tests, was used to translate the effect size into a correlation (Cooper and Hedges 1994; Hunter and Schmidt 2004; Rosenthal 1991; Sutton, Abrams, Jones, Sheldon, and Song 2000). The analysis of the data involved several steps. First, we converted all reported correlations to Fisher-transformed correlations (Hunter and Schmidt 2004; Sutton et al. 2000). Second, we identified and analyzed the variation in correlations of each relationship by an assessment and formal test of the homogeneity of pooled effects. Third, we assessed possible effects of moderators. This step was followed by a multivariate analysis of the antecedents of innovation adoption, distinguishing between intention and behavior. Below, we discuss details of each step and present the findings.

4. Effect sizes of bivariate relations

For each pair of constructs, we calculated the pooled correlation coefficient to assess the strength of the bivariate relationship using the procedures suggested by Sutton et al. (2000, p. 73-76). This approach increases the weight of more precise estimates, as all study effects are weighted by an estimate of the inverse of their variance (see Appendix for details). Table 3 presents the findings, showing the range of correlations observed, the calculated weighted average correlation, and a significance test of the observed bivariate effect size based upon the Z-statistic (see Appendix). The final column of Table 3 shows which weighted average correlations differ significantly between intention and behavior.

[Insert Table 3 here]

The effect sizes of the bivariate relations show the following results:

- Relative advantage and compatibility are positively related to innovation adoption; the strength of the relationship with intention relative to behavior is significantly weaker for relative advantage (unexpected) and stronger for compatibility (expected).
- Trialability and observability are not significantly related to intention or behavior (unexpected).
- Complexity shows a significantly stronger negative relation with behavior than with intention (expected).
- Uncertainty shows a negative relation with both intention and behavior (expected), but its relation with intention is significantly stronger (unexpected).
- Adopter characteristics show no significant relation with intention except for information seeking and media proneness (positive; the effect of innovativeness could not be tested).
- Adopter socio-demographics age (negative) and income (positive) and adopter psychographics product involvement, innovativeness, opinion leadership, information

seeking, and media proneness show significant positive relations with innovation adoption behavior.

We elaborate on these findings together with the results of the multivariate analyses after testing for potential moderators below.

5. Differences caused by study context and method

To assess the robustness of the relation of each driver with either adoption intention or adoption behavior, we examined the homogeneity of the effects using the I^2 index (Huedo-Medina, Sánchez-Meca, Marín-Martínez, and Botella 2006). The I^2 index quantifies the degree of heterogeneity based on the Q-value, which is a statistic to assess whether the effect sizes are homogenous (Cooper and Hedges 1994, p. 266), with its expected value assuming homogeneity, where $I^2 = 0$ implies perfect homogeneity, and $I^2 = 1$ relates to substantial heterogeneity (Huedo-Medina et al. 2006). The latter is an indication that moderators may affect the size and direction of the reported relationship. The first column in Table 4 shows the I^2 index for all relations considered (for both dependent variables [intention/behavior] separately), indicating that most relations are heterogeneous. We therefore next examined potential causes of this heterogeneity.

[Insert Table 4 here]

Systematic differences in substantive and methodological characteristics of studies and of individual measures of the effect may cause variation in reported effects (Bijmolt and Pieters 2001; Sutton et al. 2000). We therefore examined several potential moderating effects related to contextual and methodological factors (Hedges and Olkin 1985). We included a dummy variable for product type (durable versus other, including fast moving consumer goods and fashion) and accounted for the type of respondent (student versus non-student), the type of statistical data that we used to calculate correlations (e.g., t-tests, chi-squared tests, F-tests, or p-values), the sampling method used to collect data, the country in which the research was executed (US versus non-US), and the year of publication. If a set of relationships showed insufficient variation on a particular moderator, that moderator was excluded from the analysis (depicted by 'non-applicable' [n/a] in Table 4). To investigate whether our results were affected by moderators, we estimated a multilevel random effects model for each reported relationship between two constructs. This type of model controls for heterogeneity both within and between individual studies (Bijmolt and Pieters 2001; Hox 2002). In some cases, a study reported on multiple relationships; these relationships shared the same study characteristics, such as year of publication and data collection approach. By controlling for heterogeneity within the study, we accounted for multiple relationships originating from that study in our analysis. We then analyzed the effect of each driver (e.g., relative advantage, compatibility, and so forth) on adoption intention and on adoption behavior separately. The following model was estimated.

Suppose for each study, denoted as s, one or more relationships (r) were reported, expressed as $y_{rs}, r = 1,\ldots,R_s$. Let $R = \sum_{s=1}^{S} R_s$ reflect the total number of relationships found and the scores on $k = 1,\ldots,K$ moderator variables be denoted as $x_{k,rs}$. Then the random effects model may be expressed as:

$$y_{rs} = \beta_0 + \sum_{k=1}^{K} \beta_k x_{k,rs} + e_{rs} + u_s, \qquad (1)$$

where the error terms e_{rs} and u_s are assumed to have a normal distribution with a mean of zero and variances of σ_e^2 and σ_u^2, respectively.

Table 4 reveals that contextual and methodological moderators partly explain the variation of effect sizes reported in the literature (significant effects at the 5% level are shown in bold). The analyses reveal the following significant moderator effects (with significant effect sizes in parentheses):

- Product type affects relations of complexity (.50), age (.34), opinion leadership (-.94), and media proneness (-.74) with adoption intention, but not with behavior. This suggests that complexity is more influential for durables compared to non-durables (cf. Wood and Moreau 2006). The effect found for age may reflect consumer need for stimulation (Raju 1980), which durables may provide better. Opinion leadership and media proneness show less influence on intention for durables.
- The use of p-values to calculate correlations affected relations between adoption intention and relative advantage (-.40), complexity (-.05), and information seeking (.04). Especially for relative advantage, this result implies that estimates pertaining to its relation with intention may be more conservative due to underestimation.
- Respondent type and sampling type do not show significant effects. The country considered (other than the US) only shows a significant change in effect for complexity on intention (-.14). The year of publication shows a significant, negative effect for uncertainty (-.02) on adoption behavior.

The moderator analyses indicated that product type might be a contextual moderator of the effect of complexity on adoption intention. The results on methodological moderators display few significant effects that are neither consistent nor strong across antecedents. Taken together, these results lend credence to the generalizability of the effects derived from the meta-analysis to which we turn next.

6. Results of multivariate analyses

Based upon the availability of sufficient relationships between antecedents of innovation adoption, we estimated multivariate regression models to analyze the relationships between the adoption antecedents and intention and behavior. Throughout the adoption literature, relatively few studies have addressed the relation between innovation characteristics and adopter characteristics. Thus, relatively little insight exists into the extent to which perceptions of innovation characteristics held by consumers are affected by factors such as age, education, innovativeness or media proneness. In addition, although information seeking and media proneness occurred frequently in our data (> 10 times), too few correlations with other drivers were available. Hence, we excluded information seeking and media proneness from the multivariate regression analysis. In addition, due to an insufficient availability of correlations between adoption innovation drivers, our database does not contain a full correlation matrix of all major antecedents of intention and behavior. This is particularly troublesome in multivariate regression analysis because it accounts for dependencies between independent variables, based upon the correlations among them. Therefore, we estimated separate regression models for three groups of drivers for which correlation matrices were relatively complete, namely innovation characteristics, adopter socio-demographics, and adopter psychographics. We used a pooled correlation matrix of weighted average correlations (see Table 3) of the selected variables to estimate each model and the mean sample size of each of these pooled sets of relationships to compute standard errors. Furthermore, although product type was found to moderate some relationships, we did not have sufficient data to estimate separate models for different product types.

The results of the multivariate regression models are reported in Table 5. Because of a high correlation between relative advantage and compatibility, the models related to innovation characteristics were estimated with one of these variables at a time. Below, we elaborate on the results of the meta-analysis for adoption intention and adoption behavior.

[Insert Table 5 here]

Intention. With regard to adoption intention, we found innovation characteristics to be important drivers. The multivariate regression model that included innovation characteristics explained 36% of the observed variance for adoption intention. Among the innovation characteristics, uncertainty is the most important factor, showing a negative effect on intention.

Additionally, compatibility is strongly related to adoption intention. The perceived relative advantage of an innovation is also positively related to adoption intention but to a lesser extent. We found complexity to have a positive effect on intention in the multivariate analysis. The effect of observability on intention is not significant, whereas trialability shows a small significant positive effect in the multivariate analysis (the effect of the bivariate correlation was insignificant). Hence, we found partial support for Rogers' (2003) framework of adoption drivers with respect to adoption intentions.

With regard to adopter characteristics, we found limited effects for adopter socio-demographics. We did find significant effects for age and education, however, though with small effect sizes and low explanatory power. We also found adopter psychographics to be highly important for explaining adoption intention. In the multivariate regression analysis, these variables account for 59% of explained variance. The most relevant drivers in this analysis are consumers' product involvement and innovativeness. The bivariate analysis showed positive and significant correlations for information seeking and media proneness; however, these variables were not included in the multivariate model due to limited availability of data. Opinion leadership is not significant.

Taken together, these results demonstrate that adopter socio-demographics do not seem to be important in explaining adoption intention, whereas selected adopter psychographics and innovation characteristics do.

Behavior. For many drivers, the impact on adoption behavior differs from the impact on adoption intention. With regard to adoption behavior, we found innovation characteristics to be important drivers of adoption, although their explanatory power in the multivariate model is substantially lower than in the case of the adoption intention model (10% of the observed variance of adoption behavior). With respect to innovation characteristics, the most important antecedents of adoption behavior are the consumers' perception of the relative advantage of a new product and its complexity. Complexity, however, has an opposite effect compared to its influence on adoption intention, where we found it to be a positive driver. In the adoption stage, complexity is no longer a stimulator, but has instead become an adoption barrier, as we expected. Perceived compatibility is important, but its effect size based on the bivariate results and regression is substantially lower than in the case of adoption intention, consistent with our expectations. Uncertainty has a small significant negative effect, and although trialability and observability show significant negative effects, their effect sizes for adoption behavior are relatively small.

With respect to adopter socio-demographics, both age (negative) and income (positive) are significantly related to adoption behavior. Education is marginally significantly related to adoption behavior with a very small effect size in the multivariate model, but not based on bivariate correlations. Again, adopter psychographics are more important in explaining behavior than adopter socio-demographics, which only explain 1% of the variance in the multivariate model. Product involvement, innovativeness, and opinion leadership, which all relate to a consumer's intrinsic engagement with the new product and the product category, are positively related to adoption behavior. The regression analysis shows a similar explained variance (10%) for adopter psychographics as for innovation characteristics implying that both types of drivers contribute equally in explaining adoption behavior.

7. Discussion

The objective of this meta-analysis was to investigate whether and, if so, how antecedents of innovation adoption vary across the intention and behavior stages of the adoption process. The findings of this research provide generalizations on the key drivers of consumer innovation adoption, revealing important differences between the influence and explanatory power of antecedents across the adoption process stages. These findings thus stress the relevance of distinguishing between evaluative criteria that help to explain consumers' purchase intention of an innovation and those that explain actual purchase behavior. As such, they have implications for research on innovation adoption and for managers involved in marketing innovations. Before turning to the implications, we first discuss the surprising and unexpected results of this study.

Based on the Construal Level Theory (Trope and Liberman 2003), we expected the benefits of an innovation to be most influential on a consumer's innovation adoption decision at the intention stage. We do find, as expected, that compatibility has a stronger positive effect on intention than on behavior. Relative advantage, however, has a somewhat stronger positive effect on behavior than on intention. An explanation for this finding could be that relative advantages of an innovation represent experience qualities that can best be assessed when consequences of using the innovation are evaluated, consistent with Means-end Chain Theory (e.g., Gutman 1982). As these consequences are difficult to determine prior to purchase (Gardial et al. 1994), the effect of relative advantage on intention may be less strong. Similarly, studies in health psychology on the adoption of new healthy behaviors report that individuals attach more advantages to these new behaviors in the behavior stage than in the intention stage (Prochaska et al. 1994).

The effects found for trialability and observability on behavior were also unexpected. Both trialability and observability show negative effects at this stage of the innovation adoption process, although their effect sizes are very small. An explanation may be found in research by Karahanna et al. (1999), which suggests that the relevance of trialability vanishes once the innovation is in use. Observability becomes less relevant as well because of personal experience with the innovation. Taken together, the findings lend partial support to the notion that benefits are most influential at the intention stage, especially in terms of the innovation's perceived compatibility. Contrary to expectations, perceptions of relative advantages are more pronounced at the behavior stage, which may be caused by context-specific experiences with the innovation.

Perceived complexity was found to more strongly inhibit behavior than intention, as expected. Contrary to expectations, however, we found its effect on intention to be positive. An explanation for this finding may be that prior to adoption, at the intention stage, consumers underestimate the (potentially negative) role of complexity and are overconfident about the usability of the innovation (Wood and Moreau 2006). Likewise, Thompson, Hamilton, and Rust (2005) showed that consumers value product features (which increase the innovation's complexity) more positively and attach less weight to the innovation's usability before use than after. Taylor and Todd (1995) suggest that complexity may signal higher quality. Rather than a cost, complexity could therefore signal newness and advancement. In this vein, complexity functions as a 'trigger of interest' for adoption intention (Berlyne 1971; Messinger 1998), but becomes a barrier for behavior.

Perceived uncertainty has a negative effect on both intention and behavior, as expected, although with a stronger effect on intention than on behavior. Consistent with the small effect found at the behavior stage, Demoulin and Zidda (2009) reported that perceived risk does not discriminate between adopters and non-adopters of a new loyalty card among consumers. An explanation for the relatively weak effect of uncertainty at the behavior stage may be that adopters were compared to a group of non-adopters that included consumers in any stage of the adoption process prior to behavior. These consumers were likely to be very heterogeneous in terms of their perceptions of innovation uncertainty, as some of them may not even have been aware of the innovation. Furthermore, the role of different types of uncertainty may also account for the effects found. Because we were not able to distinguish between alternative types of uncertainty (cf. Castaño et al. 2008), the results we found may have been affected by different types of uncertainty having received different attention in previous studies that were included in the meta-analysis.

With regard to adopter characteristics, we found limited support for the impact of socio-demographics. Steenkamp and Gielens (2003) showed that the moderating role of market factors, such as the number of brands in a market, has a strong effect on the influence of age and income, resulting in non-significant main effects. Based on the meta-analysis, we conclude that socio-demographics (i.e., age, education, and income) do not have a generalizable systematic impact on adoption intention and adoption behavior. Adopter psychographics, however, including product involvement, innovativeness, and opinion leadership, account for a relatively high percentage of the explained variance of adoption intention and, to a lesser extent, of adoption behavior.

Involvement has an especially strong effect on intention to adopt an innovation. Consumers who have greater familiarity with a product category need less cognitive effort to evaluate the innovation, which makes them more likely to form adoption intentions (Gatignon and Robertson 1985). Although the empirical literature reports inconsistent effects of consumer innovativeness on adoption intention (Im, Bayus, and Mason 2003), the meta-analysis suggests a positive influence on both intention and behavior (with a stronger effect on the latter). With respect to opinion leadership, we only found a positive effect on behavior. Research by Goldenberg et al. (2009) suggests that "social hubs appear to adopt earlier because of their larger number of connections rather than innate innovativeness" (p. 10).

8. Managerial implications

For practitioners, the results of this study show the importance of understanding why and how consumers weigh evaluative criteria differently when expressing innovation purchase intention compared to when showing purchase behavior. This implies that market research tapping attitudes and purchase intentions for new products or services can be poor predictors of the innovation's success after market launch, as the example of the videophone given in the introduction painfully illustrates. Though pre-tests may lead to valuable insights, managers need to be careful when using stated intentions to further develop the product, design the marketing program or to forecast sales (Infosino 1986). This is especially relevant for really new products relative to incrementally new products (Alexander et al. 2008; Hoeffler 2003).

The different effects found for innovation adoption antecedents across decisional stages also have specific implications for stimulating adoption intention and purchase behavior. In particular, our findings imply the following:

- As perceived compatibility of the innovation is one of the most influential innovation characteristics affecting intention, marketers should make clear who would benefit most from the innovation and why.
- Communicating relative advantages of the innovation is important to stimulate both adoption intention and behavior. The advantages should best be communicated in relation to the needs and life style of the potential adopter to stimulate adoption intention. At the point of behavioral change, marketers could best relate the innovation to context-specific use situations that enable consumers to evaluate the use consequences of the innovation and thus assess its particular benefits.
- The positive effect of product complexity on adoption intention implies that managers should use the new product's features to trigger and enhance interest in the innovation among consumers. However, this should be done with great care and caution, as product complexity is found to be an important barrier for adoption behavior. Moreover, marketers should carefully manage users' expectations of product complexity, as consumers may experience setbacks as part of the process of learning how to use the product once adopted (Wood and Moreau 2006).
- As perceptions of uncertainty affect intention especially negatively, marketers should reduce difficulties to understanding the benefits of adopting and using the innovation, as these have been found to be particularly relevant prior to use (Castaño et al. 2008).

The findings of this study also suggest whom to target most effectively when marketing an innovation. Consumers showing high involvement in the product category related to the innovation are more likely to intend to adopt the new product or service. Therefore, consumers with particular interest in and knowledge of a product category may serve as ambassadors of the innovation and may consequently stimulate social contagion. Opinion leaders and innovative consumers may be targeted especially to increase adoption behavior. These consumers are not only likely to adopt earlier, but they are also more likely to stimulate others to adopt the innovation based on observation of the innovation's use (e.g., Goldenberg et al. 2009).

The results of the meta-analysis imply that, in general, socio-demographics may be poor criteria for identifying and targeting potential adopters. Although younger and higher-income consumers are found to be more likely to adopt innovations, the findings of the present study do not suggest these variables to be strong predictors of innovation adoption. Nonetheless, for particular products, socio-demographics may serve as relevant segmentation criteria, such as for consumer electronics (Im et al. 2003).

9. Limitations and implications for future research

The main findings of this study and its limitations present several interesting opportunities for future research on innovation adoption. A meta-analysis is limited by the availability and quality of the original studies, and this should be kept in mind when interpreting the results presented. In addition, variance in the definitions of independent variables may have affected some of the findings. Further, not all studies provided sufficient data for correlations to be derived. Hence, not all studies that were identified could be used in our model estimates. In addition, few studies provided the correlations between all drivers of their study. The correlation matrices we used for the meta-analysis were therefore insufficiently complete to test the effects of all potential antecedents of innovation adoption simultaneously. The differences we found for the explanatory power of innovation and adopter characteristics on the adoption outcomes considered in the separate multivariate analyses call for further research on their relative influence. In this respect, future studies could focus more on relationships that have received relatively little attention (see the number of relations found for each effect in Tables 3 and 4). Some innovation characteristics have been related more to adoption intention than to behavior (e.g., complexity), whereas others have been related more to adoption behavior than to intention (e.g., uncertainty). Adopter characteristics have been related more to behavior in previous research (by comparing adopters with non-adopters) than to intentions.

The key finding of this study is that antecedents of innovation adoption show important differences in explaining intention versus behavior. This finding is based on an analysis of a cross-sectional set of innovation adoption studies distinguishing between two major adoption process stages. However, innovation adoption implies a process that is affected over time. Future research, therefore, could benefit from adopting a process perspective by focusing on understanding dynamic effects within the innovation adoption process. Such process-oriented research may shed more light on understanding why consumers do or do not progress from one stage in the adoption process to another, such as from intention to behavior (cf. Alexander et al. 2008). Controlled empirical (e.g., longitudinal) or experimental studies may enable an enhanced understanding of transition drivers and the potential moderators affecting them.

The results of this meta-analysis imply that not all innovation characteristics, as proposed by Rogers' (2003) framework, were equally important in explaining innovation adoption. However, a limitation of the present study is that we were not able to clearly distinguish between the effect of relative advantage and compatibility due to their high correlation, as also recognized in previous studies (Karahanna et al. 1999; Tornatzky and Klein 1982). One of the reasons for this finding may be that innovation characteristics are interdependent to some extent (cf. Holak and Lehmann 1990). In addition, trialability and observability were found to have a limited effect on innovation adoption. Their influence on adoption may be mediated by other innovation characteristics, such as uncertainty (reduced) and relative advantage (enhanced)(Moreau, Lehmann, and Markman 2001). Future research may therefore focus more on interdependencies among innovation characteristics and how these affect innovation adoption. In this respect, the role of potential contingencies, such as product type (as suggested by our moderator analysis but not tested due to insufficient data), past adoption behavior (e.g., Sriram, Chintagunta, and Agarwal 2010), environmental cues (e.g., Berger and Fitzsimons 2008), and purchase type (e.g., impulse buying, Rook 1987) may also be investigated more intensively.

Although generally lacking in our database, more recent research addressed different interactions between innovation and adopter characteristics (e.g., Herzenstein, Posavac, and Brakus 2007; Lambert-Pandraud and Laurent 2010; Moreau et al. 2001; Steenkamp and Gielens 2003). As these studies found important interactions between the characteristics of the consumer and the offering being evaluated, it is likely that the effect of innovation characteristics traditionally studied in adoption research varies among different types of consumers. This could therefore be a fruitful area for future research, which might also shed more light on the effect of adopter socio-demographics relative to psychographics in the innovation adoption process (cf. Im et al. 2003).

In conclusion, this meta-analysis reveals that distinguishing between intention and behavior with respect to innovation adoption offers new insights into a much-studied field. We hope the findings benefit practitioners in marketing their innovations more effectively and stimulate academics in new directions of research on consumer innovation adoption.

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Table 1
Definitions and expected effects of innovation characteristics on consumer innovation adoption

Antecedent	Definition	Main effect	Effect for intention	Effect for behavior
Relative advantage	The degree to which an innovation is perceived as being better than the idea/product it supersedes.	Positive	Stronger	Weaker
Compatibility	The degree to which an innovation is perceived as consistent with the existing values, past experiences, life style and needs of potential adopters.	Positive	Stronger	Weaker
Complexity	The degree to which an innovation is perceived as relatively difficult to understand and use.[a]	Negative	Weaker	Stronger
Trialability	The degree to which an innovation may be experimented with on a limited basis.	Positive	Weaker	Stronger
Observability	The degree to which the results of an innovation are visible to others.	Positive	Stronger	Weaker
Uncertainty	The degree to which the functional, social, and/or financial consequences of purchasing and using an innovation cannot be established.	Negative	Uncertainty expected to affect both stages	

[a] In case 'ease of use' was used as an antecedent of adoption behavior, the relationship was reverse coded as 'complexity'.

Table 2

Definitions and expected effects of adopter characteristics on consumer innovation adoption

Antecedent	Definition	Main effect
Age	The age of the (potential) adopter.	Negative
Education	The level of education a consumer has enjoyed.	Positive
Income	The income level of the (potential) adopter.	Positive
Product involvement	The degree to which a consumer experiences differentiation, familiarity, importance and commitment for a specified product category, not brand.	Positive
Innovativeness	The general propensity of a consumer to adopt new products.	Positive
Opinion leadership	The degree to which an individual is able to influence other individuals' attitudes or overt behavior informally in a desired way with relative frequency. Informal leadership is not a function of the individual's formal position or status in the social system.	Positive
Information seeking	The extent to which one seeks information about innovations (or new developments, trends etc).	Positive
Media proneness	The degree to which an individual is receptive for the media (and its message), as well as how often an individual uses certain media.	Positive

Table 3

Correlations of antecedents of innovation adoption with adoption intention/behavior

Dependent variable	**Adoption intention**				**Adoption behavior**				**Significance of difference intention and behavior[b] (p-value [z-statistic])**
Independent variable	**Range of correlations**	**Weighted average correlation**	**Significance (p-value [z-statistic])**	**Cumulative N[a]**	**Range of correlations**	**Weighted average correlation**	**Significance (p-value [z-statistic])**	**Cumulative N[a]**	
Innovation characteristics									
Relative advantage	- .13 / .68	.18	.00 [5.69]	32007 (54)	.04 / .65	.25	.00 [4.31]	4077 (14)	.04 [4.21]
Compatibility	- .01 / .59	.34	. 00 [4.19]	3024 (8)	- .06 / .58	.13	.00 [3.35]	4466 (15)	.00 [-8.91]
Complexity	- .40 / .25	.04	.10 [1.72]	17514 (26)	- .57 / .00	- .23	.01 [3.45]	3850 (8)	.00 [-15.16]
Trialability	- .01 / .40	.07	.14 [1.72]	2609 (7)	- .11 / .32	.00	.95 [.07]	3072 (5)	.11 [-2.63]
Observability	- .05 / .34	.04	.37 [.97]	2609 (7)	- .27 / .49	.05	.44 [.82]	3604 (7)	.53 [0.39]
Uncertainty	- .72 / .06	- .44	.00 [7.60]	5183 (27)	- .34 / .26	- .07	.00 [4.33]	28142 (62)	.00 [24.47]
Adopter characteristics									
Age	- .27 / .17	.03	.49 [.74]	5760 (7)	- .57 / .26	- .07	.04 [2.14]	23510 (31)	.01 [-6.80]
Education	- .11 / .19	.05	.52 [.77]	2160 (3)	- .28 / .42	.04	.25 [1.20]	11708 (20)	.51 [-0.43]
Income	- .06 / .00	- .01	.52 [.72]	2126 (4)	- .08 / .37	.10	.00 [3.57]	11319 (19)	.03 [4.65]
Product involvement	- .07 / .85	.31	.29 [1.27]	2152 (4)	.06 / .74	.33	.00 [4.53]	5561 (9)	.37 [0.79]
Innovativeness	.76 / .76	.76	n/a[c] [19.11]	360 (1)	- .18 / .36	.19	.00 [7.98]	9748 (28)	.00 [-10.58]
Opinion leadership	.07 / .77	.33	.12 [2.19]	3060 (4)	.02 / .65	.21	.00 [8.12]	11748 (26)	.02 [-5.91]
Information seeking	.07 / .10	.09	.00 [16.55]	2700 (3)	.01 / .45	.20	.00 [4.01]	4279 (16)	.03 [4.47]
Media proneness	.07 / .68	.20	.03 [2.91]	5760 (7)	- .24 / .28	.06	.00 [3.27]	10723 (52)	.00 [-8.57]

Note: The table shows the range of correlations observed in the studies included in the meta-analysis between the independent variable (innovation characteristic or adopter characteristic) and the dependent variable (adoption intention or adoption behavior). Based on the observed range of correlations, a weighted average correlation for each relation is calculated (see Appendix for the calculation procedure).

[a] Combined sample size available for each set of relations with number of identified relations in parentheses.

[b] Difference test of weighted average correlations for adoption intention versus adoption behavior based on z-statistic for the difference between Fisher's Z transformed correlation coefficients (see Howell 2001).

[c] Significance test not applicable as correlation is based on one relation.

Table 4

Results of moderation analysis on the relations between adoption antecedents and adoption intention/behavior

Dependent Variable: **Adoption intention (I)/ Adoption behavior (B)** ***Independent Variable:*** **Innovation/Adopter characteristics**	**Degree of hetero-geneity (I^2)**		**Intercept**		**Moderators**												**R^2**	
					Product category (Durables= 1; other=0)		**Respondent** (Student=1; other=0)		**Statistic** (Effect size derived from p-value=1; other=0)		**Sampling** (Mail = 1; Other=0)		**Country** (US=1; other=0)		**Year** (Difference of year of publication with sample mean)			
	I	B	I	B	I	B	I	B	I	B	I	B	I	B	I	B	I	B
Innovation characteristics																		
Relative advantage (54/14)[a]	.97	.91	.02	.23	1.20	-.25	.03	.10	**-.40**	.60	-.94	n/a	-.84	n/a	.12	.04	.88	.91
Compatibility (8/15)	.94	.82	-2.39	.37	2.35	-.03	-.65	.27	n/a	-.22	.23	n/a	n/a	n/a	.22	.00	.65	.81
Complexity (26/8)	.87	.93	-.55	-.40	**.50**	.32	.11	-.21	**-.05**	n/a	.05	n/a	**-.14**	n/a	.02	.00	.94	.97
Trialability (7/5)	.71	.77	.32	-.11	-.30	.10	-.42	.44	n/a	n/a	n/a	n/a	n/a	n/a	.01	n/a	.98	.91
Observability (7/7)	.70	.92	-.84	n/a	.82	n/a	-.48	n/a	n/a	n/a	n/a	n/a	n/a	n/a	.09	n/a	.97	.85
Uncertainty (27/62)	.94	.81	-.84	-.28	.79	.23	.64	n/a	n/a	.00	n/a	n/a	n/a	n/a	-.05	**- .02**	.56	.20
Adopter characteristics																		
Age (7/31)	.90	.96	-.29	-.08	**.34**	.25	n/a	n/a	.04	-.05	n/a	.11	n/a	.12	n/a	.00	.78	.85
Education (3/20)	.87	.93	.19	**.24**	-.20	- .01	n/a	-.03	n/a	-.18	n/a	n/a	n/a	-.39	n/a	.01	.57	.96
Income (4/19)	n/a[b]	.88	-.06	**.21**	n/a	.09	n/a	.27	n/a	-.16	n/a	n/a	n/a	-.16	n/a	.01	.38	.96
Product involvement (4/9)	n/a[b]	.90	1.28	.66	-1.26	.00	n/a	-.26	n/a	-.57	n/a	n/a	n/a	n/a	n/a	.00	.99	.71
Innovativeness (1/28)	n/a[b]	.96	-	-	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	-[c]	-[c]
Opinion leadership (4/26)	n/a[b]	.78	1.04	.36	**-.94**	- .12	n/a	n/a	n/a	-.09	n/a	-.04	n/a	-.09	n/a	.00	.99	.57
Information seeking (3/16)	.98	.85	.08	.31	n/a	.29	n/a	-.09	**.04**	-.47	n/a	.26	n/a	-.29	n/a	.00	.94	.78
Media proneness (7/52)	.96	.96	.84	-.66	**-.74**	.84	n/a	-.04	n/a	.03	n/a	-.26	n/a	n/a	n/a	-.06	.99	.14

<u>Note</u>: The entries in the table report coefficients of the multilevel random effects model for each relationship (between the independent variable and intention or behavior as dependent variable), explaining differences between the Fisher correlations for the conditions of the moderator variables included in the analysis. The entries shown in bold indicate significant effects at the 5% level. In some cases, insufficient variation was found on a particular moderator, after which that moderator was excluded from the analysis. In that case no estimate is provided for that moderator, which is depicted in the table by 'n/a' (not applicable).

[a] The number of relations on which the random effects models are based are shown in parenthesis for intention and behavior as dependent variable, respectively.

[b] No meaningful value for I^2 can be calculated here as not enough variation across effects was found due to an insufficient number of observations.

[c] Innovativeness shows heterogeneity with regard to the effects reported. However, we found insufficient variation in moderators to explain this heterogeneity and therefore no model is estimated.

Table 5

Results of multivariate regression analyses of innovation adoption antecedents on adoption intention/behavior

Dependent variable	Adoption intention				Adoption behavior			
Independent variable	**Beta**	**t-value**	**Sig. level (p-value)**	**Adj. R^2 (mean sample size)**	**Beta**	**t-value**	**Sig. level (p-value)**	**Adj. R^2 (mean sample size)**
Innovation characteristics				.36 (487)				.10 (425)
Relative advantage[a]	**.16**	13.9	.0000		**.21**	2.7	.0000	
Compatibility[a]	**.41**	37.9	.0000		**.07**	6.6	.0000	
Complexity	**.21**	18.6	.0000		**- .20**	-18.4	.0000	
Trialability	**.06**	6.2	.0003		**- .05**	-4.7	.0077	
Observability	.00	.2	.8761		**- .04**	-3.6	.0003	
Uncertainty	**- .47**	-45.5	.0000		**- .04**	-3.8	.0001	
Adopter socio-demographics				.00 (717)				.01 (664)
Age	**.04**	2.7	.0062		**- .06**	-5.4	.0018	
Education	**.06**	4.5	.0182		.02	2.0	.0504	
Income	- .02	-1.2	.2315		**.09**	8.8	.0000	
Adopter psychographics				.59 (619)				.10 (429)
Product involvement	**.73**	86.0	.0000		**.12**	11.1	.0000	
Innovativeness	**.11**	13.6	.0000		**.17**	16.5	.0000	
Opinion leadership	- .01	-1.5	.1447		**.19**	18.8	.0000	

Note: Due to insufficient correlations between independent variables, separate regression analyses are estimated for the three groups of adoption antecedents; we therefore report the R^2 adj. for each of these regression analyses as well as the mean sample sizes on which they are based. Significant effects (5% level) are shown in bold.

[a] The estimates of relative advantage and compatibility are based on hierarchical regression models including complexity, trialability, observability and uncertainty and either relative advantage or compatibility because of the high correlation between both variables. Effect sizes and t-values for complexity, trialability, observability and uncertainty are highly robust across models with relative advantage or compatibility.

Appendix

Calculation of effect sizes

Let z_r equal the Fisher-transformed correlation between two variables, let w_i denote the weight placed on each study *i*, and let *k* represent the total number of studies.

Then, the mean effect equals:

$$\bar{z}_r = \frac{\sum_{i=1}^{k}\left(w_i * z_i\right)}{\sum_{i=1}^{k} w_i}$$

with $w_i = \frac{1}{\left[\left(1/v_i^2\right) + \hat{\tau}^2\right]}$, $\hat{\tau}^2$ = between study variance, and v_i^2 = sampling variance.

The variance of mean effect equals:

$$\mathrm{var}(\bar{z}_r) = \frac{1}{\sum_{i=1}^{k} w_i}$$

A significance test is conducted as:

Z-test $$Z = \frac{\left|\bar{z}_r\right|}{\sqrt{\mathrm{var}(\bar{z}_r)}}$$