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RESEARCH ARTICLE

Using structural technology acceptance models to segment intended users of a new technology: Propositions and an empirical illustration

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Abstract

This article aims to offer an alternative method to analyse technology acceptance models, namely a segment-wise analysis. The empirical illustration of this method involves data that were collected during a company-wide implementation of a Sales Force Automation technology in Europe. The data comprise a variety of commonly used technology-related, context-related, and person-related variables. The segmentation procedure, which involved a finite mixture partial least squares estimation, provides more insight into the different ways in which people come to accept new technologies. Unlike other segmentation studies published in IS journals, the resulting segments are based on similarities and differences in the structure of the underlying theoretical models rather than (a collection of) individual variables. Further research or a re-analysis of existing data should help establish robust "technology acceptance model"-based segments as well as comprehensive profiles of the individuals in each segment.

KEYWORDS

diffusion of innovations, sales force automation, segmentation analysis, user profiles, technology acceptance and resistance

1 | INTRODUCTION

The technology acceptance model (TAM; Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) has vastly improved our understanding of how people come to accept and use new technologies, with *perceived usefulness* and *ease of use* as key drivers of attitudes, intentions, and actual behaviour. However, similar to the Theory of Reasoned Action that was developed by Ajzen and Fishbein (1980) to explain people's behaviour in general and laid the foundation for the TAM model, predicting actual behaviour based on self-reported beliefs, attitudes, and intentions has proven difficult. To strengthen its explanatory power, the original TAM model has been extended in numerous ways. Based on a review and synthesis of 8 different technology acceptance models, the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012) comprises 4 main factors that influence people's intentions to use a new technology and, consequently, their actual behaviour. These

4 factors are performance expectancy (eg, perceived usefulness), effort expectancy (eg, perceived ease of use), social influence (eg, top management support), and facilitating conditions (eg, user training). Together with other contextual and personal factors that are included as moderators of belief ➔ intention ➔ use relationships, viz. age, gender, experience, and voluntariness of use, the UTAUT has been shown to explain around 70% of the variance in use intentions and 50% of the variance in actual use (Venkatesh et al., 2003).

Yet, the implementation of new technologies in organizations often encounters substantial resistance from employees and sometimes leads to blatant failures (see, for example, Lapointe & Rivard, 2005; Schillewaert, Ahearne, Frambach, & Moenaert, 2005). Although models of technology resistance, such as Markus' (1983) Interaction Model, Joshi's (1991) Equity-Implementation Model, and Lapointe and Rivard's(2005) model of resistance, have focused on different sets of antecedents (eg, enablers versus inhibitors), both technology acceptance and technology resistance models aim at explaining people's attitudes, use intentions, and actual behaviour. Rather than proposing new extensions and adding more complexity to technology acceptance or resistance models, this article intends to take a step back by reflecting on the core foundations of these models and by exploring the different ways in which people form their attitudes and intentions and how that influences actual behaviour. To that end, this article proposes and investigates a segment-wise analysis of theTAM/ UTAUT model. Empirical estimations of technology acceptance models typically reflect the role of attitudes, intentions, social influences, and facilitating conditions for explaining the behaviour of the "average individual". However, marketing teaches us that catering to the needs of the "average individual" entails the risk of appealing to no one. Although Henry Ford once famously said: "Any customer can have a car painted any color that he wants so long as it is black" (see Ford and Crowther, 1922, p. 71), companies have moved away from "one size fits all" strategies by creating market segments and catering to their specific needs. In a similar vein, designing interventions to stimulate the acceptance and use of new technologies based on the "average individual" is probably not the most effective strategy.

Segmentation refers to dividing a population into relatively homogenous groups of individuals in terms of their characteristics, beliefs, preferences, and/ or behaviour (eg.,Gatignon & Robertson, 1991; Steenkamp & Ter Hofstede, 2002; Wind & Bell, 2007). In his dissertation, Davis (1986) already alluded to the potential value of segmentation in the context of technology acceptance models by stating that "TAM3 appears to provide a potentially powerful framework for […] identifying segments of users whose needs are relatively homogeneous and for whom specific system configurations may be targeted." (p. 175). Thus far, segmentation studies in IS have sought to create user segments based on socio-demographic or firmographic information (e.g., Bapna, Goes, Wei, & Zhang, 2011), such as the age and gender of employees or the size of the company and the type of industry. The UTAUT model also implicitly recognizes that not all attitudes, intentions, and behaviours are created equally, because it incorporates age, gender, and experience as moderators of attitude ➔ intention ➔ behaviour relationships.

Nonetheless, marketing research has shown that socio-demographics, such as age and gender, do not necessarily constitute appropriate bases for market segmentation (Wedel & Kamakura, 2000). For example, buyers of Heineken beer can be found across a wide range of age and income levels. In other words, consumers that have different characteristics may show similar behaviour, and vice versa. In addition, socio-demographic characteristics often reveal little about a person's beliefs, preferences, needs, or other factors that motivated the person's behavior, which is crucial information for companies that want to devise effective interventions for nudging the behaviour of their customers or employees in the desired direction. Contemporary marketing textbooks therefore advocate that segments should be based ideally on (latent) needs and wants, ie, the benefits that consumers seek in a product or the problems that they would like to solve. Unfortunately, people's (latent) needs and wants are not directly observable.

This is where more easily observable individual differences can be put to use. After creating segments based on people' needs and wants (obtained via a questionnaire, for example), managers should try to identify other, more easily observable variables, such as age, gender, education, or personality traits, that are capable of discriminating between the segments. If these more easily observable variables have significant discriminatory power, they can be used to predict segment membership when information regarding (latent) needs and wants is not available, but also to identify and reach segment members with tailor-made products and messages. In the context of technology acceptance, this means that employees should be segmented based on their needs, wants, or perceptions regarding, for example, efficiency gains, user friendliness, and productivity improvements, or how susceptible they are to social influences and facilitating conditions. Once relatively homogenous segments have been created based on these variables, more easily observable individual differences can be used to identify and reach segment members with customized interventions to influence their behaviour.

In sum, this article intends to offer an alternative, segment-wise approach for analysing technology acceptance models that is intuitive to understand and relatively easy to apply by researchers and practitioners alike. To illustrate this segmentation method empirically, data were collected from 265 employees of a large, multinational company that was rolling out a new Sales Force Automation (SFA) technology in 7 European countries. Finite mixture partial least squares (FIMIX-PLS, see Hahn, Johnson, Herrmann, & Huber, 2002), which assumes that the data originate from distinct sub-populations or segments (McLachlan & Peel, 2000; Ringle, Sarstedt, & Mooi, 2010), was used to analyse the data. Following the procedure outlined by Ringle et al. (2010) segments were created based on observed similarities and differences in the estimated TAM/ UTAUT model for each employee. In other words, employees were assigned to segments based on the structure of their (mental) technology acceptance model. The empirical illustration intends to show (1) the creation of segments and their profiles and (2) the relative importance of the various TAM/ UTAUT variables for explaining attitudes, intentions, and behaviour within each segment.

2 | THEORETICAL BACKGROUND AND RESEARCH PROPOSITIONS

2.1 | Existing segmentation approaches in the technology acceptance literature

A segment-wise analysis of the technology acceptance phenomenon has been advocated in the IS literature most prominently by the seminal work of Rogers (1962) and Moore (2002). Rogers' (1962) innovation diffusion theory discerns the following 5 segments based on the individual's *timing of adoption* of disruptive innovations (ie, innovations that require significant behavioural changes on the part of the user): innovators, early adopters, early majority, late majority, and laggards. In a similar vein, but focusing on people's *attitudinal disposition* towards new technologies, Moore (2002) identified the following 5 segments: *Technology Enthusiasts*, *Visionaries*, *Pragmatists*, *Conservatives*, and *Skeptics*. Both theories assume a normal, bell-shaped distribution of the population across segments, as shown in Figure 1, and posit that the segments have distinct profiles, whether it be in terms of their beliefs, attitudes, intentions, or behaviour, their psychographics or socio-demographics, or their susceptibility to contextual influences. Notwithstanding this body of research, Bapna et al. (2011) claimed that "the value of identifying segments and developing segment-specific predictive modelling has been largely underappreciated in the IS literature" (p .119).

To provide some context for interpreting the "technology acceptance model"-based segments, which will be discussed later in the empirical illustration, and to provide a link between 2 streams of research, the following 3 broad

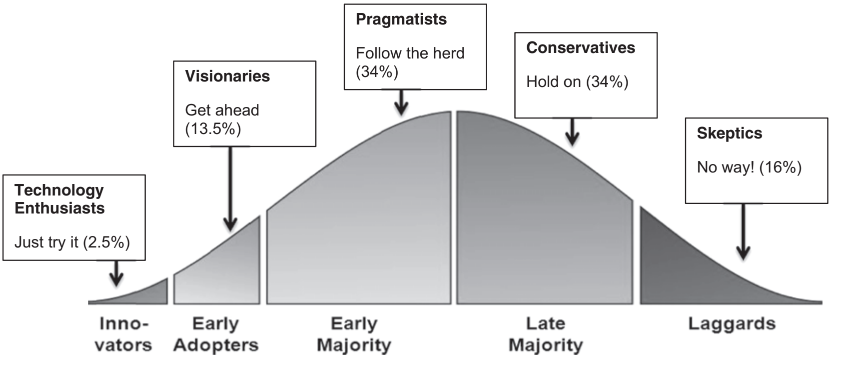

FIGURE 1 Distribution of technology acceptance segments (adapted from Moore, 2002; Taylor et al., 1994)

segments are discussed briefly here (merging the smaller segments with their adjacent segments): *Pockets of Likely Acceptance*, *Pragmatist Majority*, and *Pockets of Potential Resistance*. Figure 1 and the brief segment descriptions below are based on Moore (2002) and Taylor, Moore, and Amonsen (1994).

2.1.1 | Pockets of Likely Acceptance (ca. 16%)

The *Technology Enthusiasts* (ca. 2.5%) and *Visionaries* (ca. 13.5%) who make up this segment are most likely to accept and use new technologies. *Technology Enthusiasts* are usually the first to adopt and fully embrace new technologies. Because they are intrinsically motivated to explore new technologies, minimal effort is needed to win them over. Despite its small size, the role of this segment should not be ignored as their support could reassure members of other segments. *Visionaries* are also quick to adopt new technologies, because they can relate easily to new technologies and appreciate the benefits these technologies might offer. Technology is important inasmuch as it helps them reach their visionary goals and provides social or economical advantages. They do not require much persuasion but can be hard to please when the technology fails to meet expectations.

2.1.2 | *Pragmatist Herd (ca. 34%)*

Pragmatists value practicality and are sensitive to the new technology's quality and reliability, as well as the compatibility and integration with existing technologies. Because they require many things, if not everything, to be in place, they tend to be slower in adopting new technologies. *Pragmatists* may be harder to win over than *Visionaries* and *Technology Enthusiasts*, but they constitute an important factor for success because they represent approximately 34% of the population. In order to persuade them, endorsements from other pragmatists may be particularly important, as they tend to communicate with like-minded people.

2.1.3 | Pockets of Potential Resistance (ca. 50%)

The *Conservatives* (ca. 34%) and *Skeptics* (ca. 16%) who make up this segment are most likely to resist new technologies. *Conservatives* are, in principle, against any disruptive innovation. They prefer to stick with the old, but proven technology rather than trying out a risky new technology with uncertain benefits. Similar to *Visionaries*, they can quite stubbornly resist calls to conform to social norms, which is what largely drives the behaviour of the *Pragmatist Herd*. *Conservatives* want flawless products that do exactly what they want them to do. They only rely on trusted advisors and can be negatively influenced by *Skeptics*. For various reasons, *Skeptics* often outright reject new technologies. As they tend to be naysayers, it is very hard to please this crowd. They prefer to maintain the status quo and tend to view new technologies as a hindrance to their way of doing things. Investing heavily in trying to convince them does not seem worth the effort. However, it can be important to find ways to ensure that they do not negatively influence other people.

When implementing a new technology in an organization, it appears important for the responsible managers to anticipate and identify such differences between segments and target each segment with a customized approach to improve effectiveness (Armstrong & Kotler, 2015; Taylor et al., 1994). In the empirical illustration discussed later, the implementation of the company's new SFA technology was rolled out gradually across Europe, starting in countries that were expected to be most receptive before implementing it in countries that were anticipated to be more resistant. Thus, the company opted for a segment-wise approach to facilitate the implementation of the new technology, but on a country-level rather than the employee-level, as discussed in this article. It should also be noted here that although the old system was being replaced eventually, during the transition period, and after that, employees were free to determine the frequency with which they used the new technology (for recording, updating, looking up, and analysing sales data, for example). Hence, it is likely that there exists substantial variation in the extent of use, arguably with *Pockets of Likely Acceptance* using the new technology more extensively than *Pockets of Potential Resistance*.

2.2 | Towards a "technology acceptance model"-based segmentation approach

The number of variables and relationships included in technology acceptance and use models allow, in theory, for the existence of more segments than the ones discussed in the previous section. The actual number of segments will depend on how much heterogeneity there is in the population regarding the weight that each variable receives in the formation of attitudes and use intentions and how this drives the actual use of the new technology (eg, employees putting more weight on the ease of use of the new technology than on its usefulness, and vice versa). Although the exact formation of attitudes and intentions, and how this drives behaviour, is arguably different for each individual, segmentation techniques operate on the principle of minimizing within-group heterogeneity, while maximizing differences between groups. Hence, the exact number of segments is to be determined empirically. However, it is possible to develop some basic expectations for the 3 segments identified in the previous section as to the relative importance of the different types of variables included in technology acceptance models (eg, TAM/ UTAUT), namely technology-related, context-related, and person-related variables.

2.2.1 | Technology-related factors

Technology-related factors, such as perceived usefulness and ease of use, are pervasive in the literature on technology acceptance and use. It is to be expected that these variables play a dominant role for explaining the attitudes, intentions, and behaviour of those whose primary focus is on the features of the new technology itself, with *Pockets of Likely Acceptance* (and *Technology Enthusiasts* in particular) being positively predisposed towards using new technologies and *Pockets of Potential Resistance* (and *Skeptics* in particular) negatively. As to which technology-related factors play the most important role in each segment, one would expect that perceived usefulness (eg, increased productivity or job performance) constitutes an important driver of attitudes, intentions, and behaviour for *Pockets of Likely Acceptance*, while perceived ease of use is likely to play a more dominant role for individuals in other segments.

2.2.2 | Context-related factors

Contextual factors, such as social influences (eg, top management support or peer pressure) and facilitating conditions (eg, training sessions and technical assistance), may override people's predisposition towards the new technology in driving intentions and actual behaviour (Venkatesh, Brown, Maruping, & Bala, 2008). Social influences refer to other people, such as co-workers or supervisors, on whom an individual may rely for forming an intention to use the new technology or who can exert an influence on the individual's behaviour (Agarwal, 2000; Wang, Meister, & Gray, 2013). Facilitating conditions concern the means that organizations have put in place to facilitate technology acceptance and use, such as training sessions and helpdesk support. Managerial or co-worker encouragement (e.g., Homburg, Wieseke, & Kuehnl, 2010; Leonard-Barton & Deschamps, 1988) as well as training sessions (e.g., Homburg et al., 2010; Schillewaert et al., 2005), for example, have been shown to influence technology acceptance and use positively. However, it is unlikely that all employees are equally motivated to comply with social norms or will make equal use of the means that the organization offers in support of the technology. More specifically, one would expect that *Pockets of Likely Acceptance* and *Pockets of Potential Resistance* are less susceptible to context-related factors, as their motivation to (not) use the new technology is mostly intrinsic, whereas the *Pragmatist Herd* is more likely to be influenced by others, and their peers in particular (Schmitz & Fulk, 1991).

2.2.3 | Person-related factors

Person-related factors, such as personality traits, cognitive styles, and socio-demographics, were quite prominent in early technology acceptance research (e.g., Robey, 1983; Zmud, 1979), but their role as core explanatory variables in IS research has waned (notable exceptions are, for example, Barnett, Pearson, Pearson, & Kellermans, 2015; McElroy, Hendrickson, Towsend, & DeMarie, 2007; Venkatesh, Sykes, & Venkatraman, 2014). Because they typically reveal little about the beliefs and motivations that underlie a person's behaviour and may therefore lack sufficient explanatory power (see Huber, 1983), segments preferably should not be created based on person-related factors only. Nonetheless, because person-related factors, such as gender and education, are more easily observable and relatively stable over time, they can be useful for constructing a profile of each "technology acceptance model"-based segment. These profiles can be used for predicting segment membership of new employees and facilitate the identification and targeting of existing employees who are likely to champion or resist a new technology (McElroy et al., 2007; Steenkamp & Ter, 2002). For example, older employees with lower education levels may be overrepresented among *Pockets of Potential Resistance*, while younger employees with higher education levels may be overrepresented among *Pockets of Likely Acceptance*.

Personality traits refer to habitual patterns of thought, emotions, and behaviour (Kassin, 2003). McCrae and Costa (1987) discerned 5 major personality traits (the so-called "Big Five"), namely openness to new experiences (eg, intellectually curious and novelty seeking), agreeableness (eg, helpful and sympathetic), conscientiousness (eg, disciplined and organized), neuroticism (eg, emotionally unstable and anxious), and extraversion (eg, sociable and assertive). Personality traits have been included as explanatory variables in technology acceptance and use models (e.g., Barnett et al., 2015; Devaraj, Easley, & Crant, 2008; McElroy et al., 2007) and are referred to in Rogers' (1962) and Moore's (2002) segment descriptions, but definitive personality profiles of these segments, which are based on empirical evidence rather than theory, have yet to be established. It is conceivable that openness (eg, trying out new things), for example, is more important for predicting the attitudes, intentions, and behaviour of *Pockets of Likely Acceptance*, while agreeableness (eg, pleasing others) and neuroticism (eg, anxiety) are likely to play a more dominant role for the *Pragmatist Herd* and *Pockets of Potential Resistance*, respectively (cf. Barnett et al., 2015). IT-specific personality trait measures, such as personal innovativeness in IT (Agarwal & Prasad, 1999) (on which *Pockets of Likely Acceptance* are likely to score higher) or computer anxiety (Heinssen, Glass, & Knight, 1987) (on which *Pockets of Potential Resistance* are likely to score higher), may have better explanatory or discriminatory power than broader traits, but they are less commonly assessed in company settings.

A person's cognitive style concerns the way in which he or she tends to think, process information, and solve problems. Individuals with an analytical cognitive style tend to study a problem carefully and search for an optimal solution following a step-by-step procedure, while individuals with a heuristic cognitive style tend to take a holistic approach, seeking solutions by means of trial and error or analogical reasoning (Van Bruggen, Smidts, & Wierenga, 1998). *Pockets of Likely Acceptance* may have a more heuristic cognitive style ("just try it"), while *Pockets of Potential Resistance* may have a more analytical approach. Socio-demographics, such as age, gender, and education level, are person-related factors that are the easiest to observe. Although socio-demographics may not reveal much about underlying beliefs and motivations, they can be valuable for identifying and targeting segment members. As mentioned, *Pockets of Likely Acceptance* may contain a higher proportion of younger and highly educated employees, as they have been found to more readily embrace new technologies than older or less educated employees (e.g., Buehrer, Senecal, Pullins, & Bolman, 2005).

Successfully segmenting a population hinges on the presence of substantial similarities as well as meaningful differences between individuals. Unlike traditional segmentation studies, the approach outlined in this article is not based on similarities and differences in people's scores on (a group of) individual variables, such as attitude, intention, behaviour, and/ or socio-demographics. The basis for segmentation is the entire structural or theoretical model of how people come to acceptance and use new technologies, comprising all variables and relationships. For example, technology-related variables included in the TAM/ UTAUT model, such as perceived usefulness, can be expected to play a more dominant role for explaining the intentions and behaviour of *Pockets of Likely Acceptance* and *Pockets of Potential Resistance*, whereas context-related factors arguably play a more important role for the *Pragmatist Herd*, who are likely to be more concerned with the opinion and behaviour of relevant others than with the new technology itself. If technology acceptance models exhibit substantial heterogeneity across individuals with regards to the significance and strength of the variables for explaining attitudes, intentions, and behaviour, then a segmented approach should lead to a better overall fit and increase explained variance, as compared with estimating a single model that represents the "average individual". The previous discussion leads to the following propositions.

Proposition 1. *There exists substantial heterogeneity in the (mental) models that underlie the attitudes, intentions, and behaviour of individuals with regard to technology acceptance and use, which allows for a segmented approach and analysis (based on statistical criteria).*

Proposition 2. *The relative importance of the drivers of technology acceptance and use within segments differs significantly from that of the overall model for the "average individual".*

Proposition 3. *The "technology acceptance model"-based segments can be profiled based on significant differences in terms of technology-related, context-related, and person-related factors.*

3 | METHOD

3.1 | Study background

In order to collect data, cooperation was sought with a large, multinational company that was about to implement a new SFA technology in Europe. The company gave permission to collect survey data on a variety of technology-related, context-related, and person-related variables in 7 European countries and agreed to provide computer-recorded data on the frequency of use of the new SFA technology for all their employees in Europe. The company employs a large sales force that sells high-tech products and services to clients from a wide variety of industries, such as manufacturing, energy, health care, higher education, and financial services. The new fully integrated online SFA technology, which required substantial behavioural changes from salespeople, was replacing an old Excel-based system. As mentioned earlier, salespeople had no choice but to adopt the new SFA technology eventually, but they were free to determine the frequency of use (cf. Parthasarathy & Sohi, 1997). To increase the likelihood of a successful implementation, management opted for a phased roll-out, starting in countries where they expected resistance to be weak. Appendix A shows the timeline for the launch of the new technology and for this study's data collection.

SFA technologies intend to improve the performance of salespeople, and ultimately that of the organization (Homburg et al., 2010; Mathieu, Taylor, & Ahearne, 2007), by offering support in terms of (1) contact, account, and activity management, (2) time and event management, (3) prospecting, (4) price and product configuration, (5) sales analyses and forecasting, and (6) order and contract management (Buttle, Ang, & Iriana, 2006; Schillewaert et al., 2005). SFA technologies have been shown to be capable of improving sales performance by 15% to 35% (see Cascio, Mariadoss, & Mouri, 2010). Nonetheless, SFA implementation failures are not uncommon, with reported failure rates of 55% to even 80% (see Buttle et al., 2006; Homburg et al., 2010). This had led researchers to describe SFA technology implementations as a "hidden minefield" (Speier & Venkatesh, 2002). According to a survey across industries (Bush, Moore, & Rocco, 2005), management typically aims at buy-in percentages between 50% and 70%. The lower bound of 50% corresponds with a buy-in of both the *Pockets of Likely Acceptance* (16%) and the *Pragmatist Herd* (34%).

3.2 | Study design and data collection

After composing a draft survey (implemented in Qualtrics), it was sent for approval to the responsible managers within the company. Their feedback resulted in a number of minor changes. Personalized e-mail invitations were sent out in order to be able to match the survey data with the company's computer-recorded data on the employees' actual use of the new technology later. The survey was made available in English as well as the native language(s) of each country (if existing translations of measurement instruments were not available, the translation was carried out by people that were bilingual). There were 2 slightly different versions of the survey: (1) for countries in which the SFA technology had just been launched (France and Germany) and (2) for countries in which the SFA technology had been launched earlier (The Netherlands, Austria, UK, Italy, and Belgium). Participation in the study was strictly voluntary. As an incentive, several prizes (gift vouchers) were awarded based on the responses to the 3 quiz questions that concluded the survey (measuring cognitive style, see Appendix B). The survey invitation was followed by 2 gentle reminders.

On average, it took participants 15 to 20 minutes to complete the survey, which included all technology-related, context-related, and person-related variables listed in Appendix B. Ninety-three responses were recorded for the countries in which the new technology had just been launched (response rate: 30%), while 172 responses were recorded for the countries in which the new technology had been launched earlier (response rate: 34%). Response rates of 30% are in line with previously published SFA technology acceptance studies (e.g., Homburg et al., 2010; Schillewaert et al., 2005). The company provided computer-recorded data on the actual use of the new technology for all their employees in Europe (also for those in countries that were not part of this study) for a period of 6 months (cf. Homburg et al., 2010). Actual use was measured in terms of the frequency of use, ie, the number of times that a salesperson had accessed the new technology (cf. Barnett et al., 2015; Schillewaert et al., 2005; Straub, Limayem, & Karahanna, 1995). According to the company's managers, a higher frequency of use should lead to greater gains in employee effectiveness and efficiency. Automatic log-outs after a short period of inactivity ensured that the data represent active use.

3.3 | Sample characteristics

Table 1 shows the characteristics of the sample, split by timing of the survey: right after launch (early adoption phase) and several months after launch (late adoption phase). As can be seen in Table 1, the composition of these subsamples slightly differs in terms of gender, age, and education level. Assuming that late respondents to the survey are most similar to non-respondents (Miller & Smith, 1983), the data of early respondents (ie, those who responded after the first survey invitation) were compared with those of late respondents (ie, those who responded after the second reminder) to assess whether non-response bias could pose a threat to the study's internal validity. Except for age and country, there were no significant differences between early and late respondents for the variables included in the survey as well as for the computer-recorded actual use of the new technology. Younger salespeople and salespeople from Belgium were overrepresented among late respondents, whereas salespeople from The Netherlands were overrepresented among early respondents (all *p*'s < .05). A comparison of the actual use of the new technology (over the 6-month data collection period) of the survey respondents with that of all European's registered users revealed that the respondents to the survey had, on average, a higher computer-recorded frequency of use of the new technology (range: 0 to 1028; M_{sample} = 115 (SD = 111, *n* = 226)[1] versus $M_{overall}$ = 83 (SD = 104, *n* = 775), $t(999) = 4.035$, $p < .001$). Possible reasons could be that (1) the sample was generally more inclined to use the SFA technology than the overall population, possibly leading to an underestimation of the actual level of resistance within the company, and (2) the existence of technical difficulties or implementation delays in some countries (as, for example, in Austria).

TABLE 1 Sample characteristics

	Survey (T0)	
Characteristics	**Early Adoption Phase (Right after Launch) *N* = 93**	**Late Adoption Phase (Several Months after Launch) *N* = 172**
Gender: Male	63%	83%
Age: under 40	45%	39%
Education level: ≥ Bachelor	65%	47%
Countries:	France, Germany	Austria, Belgium, Italy, Netherlands, UK
Number of employees: > 100	63%	67%
Tenure company: > 5 years	63%	69%
Attended training session	87%	89%
Response rate	*30%*	*34%*

N = 265.

3.4 | Measures

The survey featured measures for the constructs of the TAM/ UTAUT models (see Venkatesh et al., 2003), namely perceived usefulness (or performance expectancy), perceived ease of use (or effort expectancy), social influence (from top management, supervisors, and colleagues), facilitating conditions (ie, training sessions and previous experience with similar technologies), use intention, and individual differences (such as gender, age, and experience). In addition to these constructs, the “attitude” construct that was part of the original TAM model was also included in the survey (see Appendix B). All technology-related, context-related, and person-related constructs were measured by means of well-established scales. Appendix B lists all the constructs, measurement scales, and their source(s).

A number of precautions were taken to reduce common-method bias. First, the order of items of multiple-item scales was randomized, as well as the order of measures of closely related constructs (such as the “Big Five” personality traits). Second, a number of items were reverse coded (as indicated by an (r) in Appendix B). Third, different scale formats were used (eg, Likert scales and semantic differential scales, see Appendix B). The reliability of the multiple-item measures ranged from satisfactory (Cronbach's $\alpha > .6$) to excellent, except for the 2-item scales that were used for measuring the “facilitating conditions” construct and the “Big Five” personality traits (see Appendix B). Other studies that have used abbreviated versions of the “Big Five” measurement instrument have also reported modest reliability coefficients (e.g., Gosling, Rentfrew, & Swann, 2003; Hughes, Furnham, & Batey, 2013). Given that the items were taken from validated scales and the non-central role of these constructs in this study, the item scores were simply averaged for use in further analyses.

4 | ANALYSES AND RESULTS

4.1 | Partial least squares estimation of the technology acceptance model (TAM)

First, a PLS analysis, with “use intention” as the dependent variable and “perceived usefulness”, “perceived ease of use”, “social influence”, and “attitude towards the new technology” as the independent variables, was conducted to estimate the TAM for the overall sample (n = 260).[2,3] The estimated model is depicted in Figure 2A. This model basically follows the original TAM, with the addition of the relationship between social influence and behavioural intention (consistent with Ajzen and Fishbein's (1980) Theory of Reasoned Action). The reason for estimating this simpler TAM model instead of the more complex UTAUT model is that data on actual use were missing for a substantial number of respondents to the survey (ie, 39 out of 265). A segment-wise, FIMIX-PLS analysis of the UTAUT model, which has actual use as the dependent variable, produces a “missing value” segment that comprises most of these

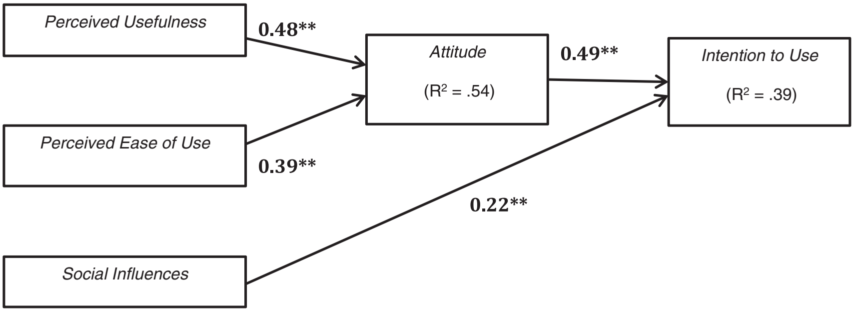

FIGURE 2A TAM model estimation. *Notes.* ** Coefficients significant at the 5% level (based on bootstrapping with 5000 samples). Estimated indirect effects: Perceived Usefulness ➔ Intention to Use: .23 ($p < .01$) and Perceived Ease of Use ➔ Intention to Use: .19 ($p < .01$)

respondents. Nonetheless, after creating segments based on the simpler TAM model, the results of a segment-wise analysis of the UTAUT model will also be reported, see Figure 2B.

For the measurement model (outer model), the loadings of the individual items on their corresponding constructs were all above .73 (the recommended threshold is .50, see Hulland, 1999), the composite reliability coefficients of the construct measures ranged from .85 (for "social influence") to .97 (for "perceived usefulness") (the recommended threshold is .70, see Nunnally and Bernstein, 1994), and the square root of the average variance extracted (AVE) for all constructs is greater than the variance shared with the other constructs, attesting to their discriminant validity (Fornell & Larcker, 1981). The results of the estimation of the structural TAM model (inner model) for the overall sample are shown in Figure 2A.

The model fits the data reasonably well, ie, the standardized root mean square residual is .07, which is below the conservative threshold of .08 (see Hu & Bentler, 1998), and the model explains 54% of the variance in the respondents' attitude towards the new SFA technology and 39% of the variance in their intention to use the technology. All estimated coefficients for the direct and indirect paths depicted in the model are significant (p's < .01) and in the expected direction (see Figure 2A). So far, the results appear consistent with the vast majority of technology acceptance research. However, the aim of this article is not to replicate previous findings or to find the best fitting model, but to investigate the presence (or absence) of distinct segments with regard to how people come to accept and use new technologies. To put it differently, the question is whether or not the coefficient estimates for the relationships that make up technology acceptance models differ substantially across groups of individuals. In the next section, the coefficient estimates will therefore be allowed to vary across segments using FIMIX-PLS.

4.2 | "Technology acceptance model"-based segmentation

A FIMIX-PLS (see Hahn et al., 2002) analysis was used to carry out a segment-wise analysis of the TAM model (as depicted in Figure 2A), following the procedure outlined by Ringle et al. (2010). The procedure consists of 3 steps: (1) PLS estimation of the overall model (ie, a single model estimation for the whole sample, as presented in the previous section), (2) determination of the number of segments by comparing the results of the FIMIX-PLS model estimations for varying numbers of segments, and (3) description and profiling of segments by means of ex-post analyses. Hence, after completing step 1, FIMIX-PLS analyses, with varying pre-specified numbers of segments, were conducted to determine the number of distinct segments in the overall sample.

The results presented in Table 2 are based on FIMIX-PLS iterations using changes of less than 1E − 10 in the parameter estimates as a stop criterion. The FIMIX-PLS iterations were repeated 100 times, because the results with lower numbers of repetitions were unstable when the number of pre-specified segments was set to 3 or higher, indicating the presence of local optima. Table 2 shows the information and classification criteria (2A), probabilities of segment membership (2B), and segment sizes (2C) for varying numbers of pre-specified segments (2–6).

In determining the appropriate number of segments to retain, the information presented in Table 2A, 2B, 2C was considered jointly. First, lower numbers for the information criteria presented in Table 2A (ie, LnL, AIC, BIC, and CAIC) indicate a better fit. Higher numbers for classification criteria, such as the normed entropy (EN) statistic

TABLE 2A Information and classification criteria for varying numbers of segments (2–6)

Number of Segments	LnL	AIC	BIC	CAIC	EN
2	−555	1136	1182	1195	0.29
3	−543	1126	1197	1217	0.52
4	−530	1114	1210	1237	0.53
5	−521	1110	1231	1265	0.54
6	−510	1102	1248	1288	0.57

Abbreviations: AIC, Akaike's Information Criterion; BIC, Bayesian Information Criterion; CAIC, Consistent Akaike's Information Criterion; EN, Entropy Statistic (Normed); LnL, LogLikelihood.

TABLE 2B Probability of segment membership for varying number of segments (2–6)

Number of Segments	[1.0, 0.8]	[0.8, 0.6]	[0.6, 0.4]	[0.4, 0.2]	[0.2, 0.0]
2	0.36	0.40	0.24	-	-
3	0.39	0.32	0.28	0.01	-
4	0.32	0.33	0.33	0.02	-
5	0.28	0.23	0.41	0.08	-
6	0.26	0.22	0.44	0.08	-

Probability of segment membership given between brackets, eg [1.0, 0.8] means probability between 80%-100%.

TABLE 2C Segment sizes for varying number of segments (2–6)

Number of Segments	S_1	S_2	S_3	S_4	S_5	S_6
2	0.52	0.48				
3	0.56	0.33	0.11			
4	0.37	0.45	0.09	0.09		
5	0.46	0.25	0.16	0.10	0.03	
6	0.36	0.22	0.24	0.09	0.07	0.02

S, segment sizes based on discrete assignment of individuals to segments.

(see Table 2A), indicate a higher degree of distinctiveness between segments and thus a more reliable assignment of individuals to segments. Ringle et al. (2010) proposed a threshold of .50 for the normed entropy statistic, which is surpassed when partitioning the sample in 3 or more segments (see Table 2A). Second, Table 2B shows the proportion of the sample for which the highest probability of segment membership falls within the displayed brackets. A good segmentation solution produces high probabilities of assigning individuals to specific segments. These probabilities decline when splitting the sample into more than 3 segments. Finally, Table 2C shows the size of each segment. Although small segments can be meaningful from both a theoretical and practical perspective, the number of observations for small segments in this empirical illustration (eg, segments comprising less than 10% of the sample, which equals 26 observations) could fail to produce robust coefficient estimates for the segment-specific TAMs.

Given the aforementioned decision criteria and the considerations put forward in the theory section, a 3-segment solution was chosen. The smallest segment contains 30 individuals (approximately 11% of the sample, see Table 2C), which is above the rule of thumb of 10 times the maximum number of arrows pointing at a latent variable in the model ($10 \times 2 = 20$) (Chin, 1998; Hair, Hult, Ringle, & Sarstedt, 2014). However, it should be noted that this is a rule of thumb and that the stability of parameter estimates improves with larger segment sizes (see Chin, 1998). Table 3 shows the coefficient estimates for the overall and segment-wise analyses of the TAM (and UTAUT) model.

4.2.1 | TAM model

Segment 1, the biggest segment that comprises 56% of the sample, places significantly more weight on perceived usefulness ($b = .61$, $p < .01$) and less weight on perceived ease of use ($b = .04$, $p = .52$) in the formation of their attitude towards the new SFA technology, as compared with the overall sample (see Table 3). In addition, the relationship between their attitude towards the new SFA technology and their intention to use it ($b = .16$, $p = .097$) is significantly weaker than for the overall sample, resulting in an explained variance in “use intention” of only 9%. By contrast, Segment 2 (33% of the sample) places significantly more weight on perceived ease of use ($b = .81$, $p < .01$) and less weight on perceived usefulness ($b = .19$, $p < .01$) in the formation of their attitude towards the new SFA technology. Moreover, there is a strong link between “attitude” and “use intention” for Segment 2 ($b = .76$, $p < .01$), explaining 92% of the variation in “use intention”. Finally, Segment 3's (11% of the sample) attitude formation appears to be more

TABLE 3 Technology acceptance model estimations and segment-specific results

Structural Relationships	Overall Model (N = 260)	FIMIX-PLS Results *Segment 1* (*N = 145*)	*Segment 2* (*N = 85*)	*Segment 3* (*N = 30*)
TAM Model				
Perceived Usefulness ➔ Attitude	.48** (.05)	.61** (.05)[b]	.19** (.05)[a]	.68** (.06)[a]
Perceived Ease of Use ➔ Attitude	.39** (.05)	.04 (.06)[a]	.81** (.04)[a]	.58** (.09)[b]
Social Influences ➔ Use Intention	.22** (.07)	.20** (.09)	.29** (.04)	.56** (.06)[a]
Attitude ➔ Use Intention	.49** (.06)	.16* (.10)[a]	.76** (.04)[a]	.53** (.07)
R^2 (Attitude)	.54	.39	.88	.98
R^2 (Use Intention)	.39	.09	.92	.96
UTAUT Model				
Perceived Usefulness ➔ Use Intention	.27** (.08)	.30** (.11)	.20** (.06)	.35** (.07)
Perceived Ease of Use ➔ Use Intention	.24** (.08)	−.06 (.14)[b]	.60** (.06)[a]	.36** (.08)
Social Influences ➔ Use Intention	.23** (.07)	.11 (.09)	.25** (.05)	.52** (.07)[a]
Facilitating Conditions ➔ Actual Use [c]	−.08 (.10)	−.17 (.14)	.08 (.15)	.39 (.42)
Use intentions ➔ Actual Use [c]	.23** (.05)	.14 (.10)	.31** (.09)	−.17 (.30)
R^2 (Use Intention)	.34	.13	.85	.97
R^2 (Actual Use)	.05	.05	.12	.10

Notes. Standard errors between parentheses.

*p < .10, **p < .05.

[a,b] Significant difference with the overall sample coefficient estimates at the 5% (a) and 10% (b) level based on the Welch-Satterthwait t-test for unequal variances and unequal sample (segment) sizes.

[c]Missing values for "Actual Use" (N = 221); Segment 1: N = 124, Segment 2: N = 72, Segment 3: N = 25.

balanced, with significant and comparable weights for perceived usefulness, perceived ease of use, and social influences (see Table 3). For Segment 3, the relationship between "social influences" and "use intention" (b = .56, p < .01) is stronger than for the overall sample. This also holds for the link between "attitude" and "use intention" (b = .53, p < .01), resulting in an explained variance of 96% for "use intention". Taking the sum of explained variances per segment weighted by the size of each segment reveals that the segment-wise analysis of the TAM model explains 62% of the variance in "attitude towards the new SFA technology" and 46% of the variance in "use intention". This represents a 15% and 18% increase, respectively, over the explanatory power of the overall, non-segmented model. Nonetheless, the low percentage of explained variance (9%) for the intention to use the new SFA technology of the biggest segment (Segment 1) is a reason for concern.

4.2.2 | UTAUT model

Although use intentions are an important indicator, the ultimate variable of interest for the company is the actual use of the new technology. Hence, the UTAUT model, as depicted in Figure 2B, was analysed for both the overall sample and the created segments based on the TAM model estimations. As mentioned earlier, the segments were not created based on the UTAUT model itself due to the fact that for a substantial number of individuals data on the actual use of the new SFA technology were missing, which produced a segment that contains most of these individuals. It should also be noted that the person-related variables included in the UTAUT model, such as age and gender, which are assumed to moderate the core relationships of the UTAUT model, were omitted from the analysis. However, these person-related variables will be used later for describing and profiling the segments. The overall UTAUT model

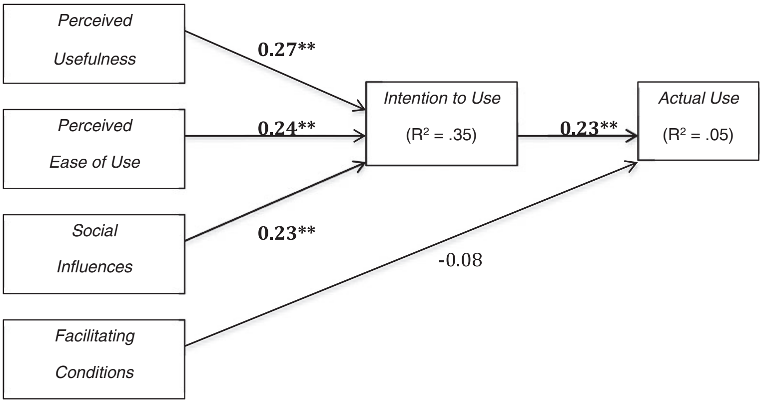

FIGURE 2B UTAUT model. *Notes.* ** Coefficients significant at the 5% level (based on bootstrapping with 5000 samples). Estimated Indirect effects: Perceived Usefulness ➔ Actual Use: 0.06 (p < .01), Perceived Ease of Use ➔ Actual Use: 0.06 (p = .01), Social Influences ➔ Actual Use: 0.05 (p < .01)

explains 34% of the variance in "use intention" and 5% of the variance in "actual use" of the new SFA technology (see Figure 2B). All estimated coefficients for the direct and indirect paths depicted in the model are significant (*p*'s < .01) and in the expected direction, except for the direct effect of "facilitating conditions" on "actual use" (see Figure 2B). Furthermore, the link between "use intention" and "actual use" is significant and positive (b = .23, p < .01). Table 3 (bottom part) shows the results per segment.

As compared with the model estimated for the overall sample, perceived ease of use plays a less important role in the intention to use the new SFA technology for members of Segment 1 (b = −.06, p = .68), while the opposite holds true for members of Segment 2 (b = .60, p < .01). Social influences have a bigger impact on "use intention" for members of Segment 3 (b = .52, p < .01). Noteworthy here is that only for members of Segment 2, there exists a significant positive relationship between self-reported "use intention" and "actual use" (b = .31, p < .01). The segment-wise analysis of the UTAUT model explains 46% of the variance in "use intention" and 8% of the variance in "actual use", which represents a 35% and 60% increase, respectively, in explanatory power over the overall, non-segmented model.

To conclude, in line with *Proposition 1*, there exists substantial heterogeneity in the (mental) models that underlie the attitudes, intentions, and behaviour of individuals with regard to technology acceptance and use, which allows for a segment-wise analysis to improve the explanatory power of technology acceptance models, such as the TAM and UTAUT. Furthermore, consistent with *Proposition 2*, the relative importance of the drivers of technology acceptance and use within segments differs significantly from the overall model that represents the "average individual." This begs the question (see *Proposition 3*) as to whether or not it is possible to describe and profile these segments based on their perceptions, attitudes, intentions, and behavior, and can socio-demographic data, for example, be used to effectively identify and reach segment members in order to target them with customized intervention strategies.

4.3 | Profiling "technology acceptance model"-based segments

In order to describe and profile each segment, it is not only important to take into consideration the drivers of attitudes, intentions, and behaviour per segment, but also the segments' average scores on the technology-related, context-related, and person-related factors that were included in the survey. Table 4 shows the segment means and standard deviations for these variables and the F-values to test for significant differences in the segment means.

TABLE 4 Segment means and standard deviations for the study's main variables

Variables	Segment 1	Segment 2	Segment 3	F-Value
Technology-related factors				
TAM/UTAUT variables:				
- Perceived usefulness	2.9 (1.0)	3.0 (1.1)	3.3 (0.7)[1]	*2.5**
- Perceived ease of use	3.3 (0.8)	3.4 (0.9)	3.5 (0.9)	*0.7*
- Attitude towards the technology	3.2 (0.6)	3.2 (0.9)	3.7 (0.8)[1,2]	*4.6***
- Use intention	3.7 (0.8)	3.6 (1.1)	4.0 (0.5)[1,2]	*2.1*
- Actual use	17.4 (15.3)	17.6 (13.6)	21.3 (18.1)	*0.7*
Context-related factors				
- Social influences	3.6 (0.7)	3.6 (0.7)	3.9 (0.6)[1,2]	*1.9*
- Facilitating conditions	3.4 (0.7)	3.6 (0.7)	3.6 (0.8)	*1.3*
Person-related factors				
Personality traits:				
- Openness	3.9 (0.6)	4.0 (0.6)	3.6 (0.6)[1,1]	*3.8***
- Agreeableness	4.1 (0.6)	4.1 (0.5)	4.1 (0.5)	*0.2*
- Neuroticism	2.7 (0.8)	2.5 (0.8)[1]	2.6 (0.6)	*2.5**
- Conscientiousness	4.3 (0.6)	4.3 (0.5)	4.3 (0.5)	*0.1*
- Extraversion	4.1 (0.6)	4.1 (0.5)	4.1 (0.5)	*0.0*
- Self-rated innovativeness in IT	3.1 (0.9)	3.2 (0.9)	3.1 (0.7)	*0.2*
- Actualized innovativeness	5.4 (2.1)	5.7 (1.9)	5.9 (1.9)	*0.8*
Cognitive style:				
- Analytical (versus heuristic)	1.8 (0.8)	1.8 (0.7)	1.7 (0.7)	*0.2*
Socio-demographics:				
- Age category	4.0 (1.8)	3.7 (1.6)	3.9 (1.6)	*0.8*
- Gender	0.25 (0.4)	0.21 (0.4)	0.25 (0.4)	*0.2*
- Education level	3.6 (1.1)	3.6 (1.1)	3.3 (1.3)	*0.9*
- Tenure	4.2 (1.5)	4.2 (1.3)	4.3 (1.3)	*0.0*
Country:				
- France	0.28 (0.5)	0.31 (0.5)	0.27 (0.5)	*0.1*
- UK	0.30 (0.5)	0.28 (0.5)	0.27 (0.5)	*0.1*
- Italy	0.26 (0.4)	0.25 (0.4)	0.37 (0.5)	*0.8*
Other variables:				
- Attended training session	0.87 (0.3)	0.88 (0.3)	0.96 (0.2)[1,2]	*1.0*
- Experience with the new technology	3.2 (1.7)	3.2 (1.7)	3.3 (1.6)	*0.1*

Notes. Standard deviations between parentheses.

[1,2] Significant difference with segment 1 or 2 at the 5% level (10% level in italics), corrected for inequality in variances, where necessary.

4.3.1 | Technology-related factors

Table 4 shows significant differences across segments in terms of the average scores on attitude towards the new SFA technology and the intention to use it. Individuals in Segment 3, on average, are more positively predisposed towards the new SFA technology than the other 2 segments (attitude: $M_{segment3} = 3.7$ versus $M_{segment1} = 3.2$ and $M_{segment2} = 3.2$, p's < .05; use intention: $M_{segment3} = 4.0$ versus $M_{segment1} = 3.7$ and $M_{segment2} = 3.6$, p's < .05, see Table 4). Another significant difference exists between Segment 1 and Segment 3 in terms of the perceived usefulness of the new SFA technology ($M_{segment3} = 3.3$ versus $M_{segment1} = 2.9$, $p = .05$). Although the means for "actual use" are not significantly different across segments (see Table 4), it appears that Segment 3 tends to use the new SFA technology more frequently than the other 2 segments. Given the more positive subjective evaluations of the new SFA technology, the size of the segment (11%), the focus on all aspects when forming attitudes and intentions (ie, perceived usefulness, perceived ease of use, and social influences, see Table 3), and the relatively strong relationship between "attitude" and "use intention" (see Table 3), Segment 3 is arguably best described as *Pockets of Likely Acceptance*.

4.3.2 | Context-related factors

The context-related factors concern social influences and facilitating conditions, which are both included in the UTAUT model (see Figure 2B). Only for "social influences" there is a significant difference across segments at the 10% level (see Table 4). Individuals in Segment 3, on average, tended to report a more positive influence of their colleagues and managers with regard to the use of the new SFA technology than the other 2 segments ($M_{segment3} = 3.9$ versus $M_{segment1} = 3.6$ and $M_{segment2} = 3.6$, p's < .10). This finding appears to contradict with labelling Segment 3 as *Pockets of Likely Acceptance*, whose motivation to use the new technology is said to be mostly intrinsic. However, *Pockets of Likely Acceptance* also include *Visionaries*, whose opinions and behaviour may be positively influenced by *Technology Enthusiasts*. Another relevant variable is whether or not employees attended a training session offered by the company prior to the launch of the new SFA technology (cf. Armenakis, Harris, and Mossholder's (1993) discussion on the importance of getting employees ready for change). Table 4 shows that individuals in Segment 3 were more likely to have attended a training session than individuals in the other 2 segments ($M_{segment3} = .96$ versus $M_{segment1} = .87$ and $M_{segment2} = .88$, $p = .05$ and $p = .09$, respectively; corrected for unequal variances), which corroborates the labelling of Segment 3 as *Pockets of Likely Acceptance*.

4.3.3 | Person-related factors

Because this type of information is generally easier to obtain than the subjective evaluations of a new technology of employees who have not replied to the company's survey, person-related factors can be important for identification and targeting purposes. By and large, however, the person-related factors in this study do not appear to have much discriminatory power for profiling the segments. Only 2 person-related variables revealed significant differences between segments, namely the "Big Five" personality traits "openness to new experiences" and "neuroticism" (see Table 4). Counter-intuitively, given the labelling of Segment 3 as *Pockets of Likely Acceptance*, Segment 3's mean score on self-reported "openness to new experiences" is significantly lower than for the other 2 segments ($M_{segment3} = 3.6$ versus $M_{segment1} = 3.9$ and $M_{segment2} = 4.0$, p's < .05), but their self-reported innovativeness in IT and actualized innovativeness (eg, owning state-of-the-art high-tech devices) are, on average, not significantly different from the other 2 segments (see Table 4). Segment 1 and Segment 2 differed significantly in terms of their mean scores on self-reported "neuroticism", with Segment 1 being more neurotic ($M_{segment1} = 2.7$ and $M_{segment2} = 2.5$, $p = .03$). Cognitive style and socio-demographics, including country (see Table 4: only the 3 countries with a sufficient number of respondents per segment are included in Table 4) and experience with the new technology, did not reveal any significant differences between segments. Overall, it seems that the more easily observable person-related variables reveal little as to how the employees in this organization formed their attitudes, intentions, and behaviour towards the newly implemented SFA technology.

Based on the segment means that are significantly different and the size of each segment, Segment 1 (56%) could be tentatively labelled as *Pockets of Potential Resistance* and Segment 2 (33%) as the *Pragmatist Herd*. The main reasons for this are that individuals in Segment 1 were mostly concerned with the perceived usefulness of the new SFA technology, which constitutes the main driver of their attitudes, intentions, and behaviour (see Table 3). However, Segment 1 perceives the usefulness of the new SFA technology to be significantly lower than Segment 3, ie, the *Pockets of Likely Acceptance* (see Table 4). In addition, for Segment 1 the relationships between attitude, intention, and behaviour are weak or even non-existent (see Table 3) and individuals in this segment, on average, score higher on self-reported neuroticism (see Table 4). Individuals in Segment 2, on the other hand, care most about the perceived ease of use of the new SFA technology, which is the main driver of their attitudes, intentions, and behaviour. Moreover, attitude, intention, and behaviour are more strongly aligned for Segment 2 than for the other segments (see Table 3), which attests to the pragmatism of individuals in Segment 2 (ie, they appear to do what they said they will do). These segment labels and profiles should be taken as tentative, based on information from a single survey conducted among employees from a single company concerning a specific new SFA technology. Hopefully, this empirical illustration of a segment-wise analysis of technology acceptance models will inspire other researchers to do the same, so that more definitive conclusions regarding the number of segments and their profiles can be drawn eventually.

5 | GENERAL DISCUSSION

5.1 | Main findings

Segment-oriented theories of technology acceptance and use (e.g., Moore, 2002; Rogers, 1962) divide the overall population into relatively homogeneous groups of people that are similar in terms of their beliefs, attitudes, and/ or behaviour with respect to disruptive new technologies. However, a better understanding of the factors that *drive* the attitudes, intentions, and behaviour of each segment can be instrumental for developing effective intervention strategies that aim to foster technology acceptance and use. To that end, this study deployed a variety of technology-related, context-related, and person-related factors to create and profile segments. Different from prior segmentation studies published in the IS literature, the basis for segmentation was the entire structure of technology acceptance models (ie, TAM and UTAUT) rather than a single variable, such as timing of adoption (see Chiu, Fang, & Tseng, 2010; Rogers, 1962) or one's predisposition towards new technologies (see Moore, 2002), or a group of variables, such as firmographics (see Bapna et al., 2011). The data were collected at a large, multinational company that launched a new SFA technology in several European countries. Using FIMIX-PLS, the data revealed that there exists sufficient heterogeneity in the estimated TAM/ UTAUT models to warrant a segment-wise approach (consistent with *Proposition 1*). The segment-specific analyses explained additional variance in attitudes, intentions, and behaviour as compared with a non-segmented, overall model that represents the “average individual”. Also, the relative importance of the drivers of technology acceptance and use within each segment differed significantly from the overall model estimates (*Proposition 2*), which provides insight into what levers to pull to influence the attitudes, intentions, and/ or behaviour of each segment.

To be practically relevant, it is important that the created segments have distinct profiles that enable the prediction, identification, and targeting of segment members (*Proposition 3*). In the empirical illustration, the profiles of the created segments were not found to be very different in terms of easily observable and relatively stable person-related variables, such as gender, age, tenure, and innovativeness in IT. The only person-related variables that had significant discriminatory power were the “Big Five” personality traits “openness to experience” (lower scores for Segment 3) and “neuroticism” (higher scores for Segment 1). None of the socio-demographic variables was able to significantly discriminate between segments, which is in line with Laumer, Maier, Eckhardt, and Weitzel's (2016) findings that personality traits have more explanatory or discriminatory power than socio-demographics. Among the technology-related and context-related factors, perceived usefulness, attitude towards the new technology, use intentions, and social influences demonstrated significant discriminatory power for profiling the segments, but this data can only be obtained via surveying employees. Hence, more research is needed to determine whether or not it is possible to create segment profiles that allow for targeting based on more readily observable person-related variables, such as socio-demographics. Based on theory and empirical evidence, the 3 segments were tentatively labelled as *Pockets of Potential Resistance* (Segment 1: 56%), *Pragmatist Herd* (Segment 2: 33%), and *Pockets of Likely Acceptance* (Segment 3: 11%). However, more research is needed to confirm the number of distinct segments as well as their profiles and labels, taking into account both statistical and practical considerations to assess the distinctiveness and managerial relevance of the segments.

5.2 | Theoretical contributions

Extant research on technology acceptance and use has extensively investigated main effects of a broad variety of technology-related, context-related, and person-related factors and, more recently, has started paying attention to moderating effects, as conceptualized in the UTAUT model (Venkatesh et al., 2003) for example, in order to allow relationships between variables to vary across groups of individuals (eg, based on age or gender). Notwithstanding the importance of this large body of research for advancing our understanding of technology acceptance and use, this article describes a procedure for conducting a segment-wise analysis of technology acceptance models, together with an empirical illustration. Unlike segmentation studies that create segments based on similarities and differences in attitudes, intentions, and/ or actual behaviour, the segmentation approach presented in this article (following the procedure outlined by Ringle et al, 2010) is based on similarities and differences in *how* individuals come to accept and use new technologies, ie, the entire structure of technology acceptance models (eg, TAM or UTAUT). A broad variety of descriptive variables, comprising technology-related, context-related, and person-related variables (e.g., Jasperson, Carter, & Zmud, 2005; Lamb & Kling, 2003; Lapointe & Rivard, 2005; Markus, 1983), was then used to profile the created segments (consistent with calls in IS research for moving towards a more holistic user perspective).

A segment-level investigation can help establish stronger links between subjective evaluations of new technologies and their actual use and performance, as these links have been found to be weak or even non-existent sometimes (Althuizen, Reichel, & Wierenga, 2012; Barnett et al., 2015; Stein, Newell, Wagner, & Galliers, 2015; Straub et al., 1995; Turner, Kitchenham, Brereton, Charters, & Budgen, 2010; Van Offenbeek, Boonstra, & Seo, 2013), especially when people have limited experience with the new technology (Venkatesh et al., 2008). The empirical illustration showed that the main drivers of attitudes, intentions, and behaviour, as well as the explanatory power of technology acceptance and use models, can vary across segments. For Segment 1 in particular, which represents more than half of the sample, the relationship between attitudes, intentions, and actual behaviour was found to be weak and, as a result, the explanatory power of the TAM and UTAUT models was relatively low. The relatively low explained variance implies that there are other factors (not included in the model) that are driving attitudes, intentions, and behaviour. This segment, for example, may comprise so-called “ambivalent” users (see Bagayogo, Beaudry, & Lapointe, 2013; Seo, Boonstra, & Van Offenbeek, 2011; Van Offenbeek et al., 2013) for whom there exists a general disconnect between attitudes, intentions, and actual use. That is, ambivalent users may either have (1) a supportive/ positive predisposition but low use of the new SFA technology, for example due to practical reasons, such as being too busy with other things or a lack of technological know how, or (2) a resistant/ negative predisposition but high use of the new SFA technology, for example because they felt they had no choice but to use the new technology or they already entered their (sales) data into the new system. Other omitted variables could be related to emotional responses or coping mechanisms, which may be particularly relevant in situations where technology acceptance and use is mandatory (see, for example, Bhattacherjee, Davis, Connolly, & Hikmet, 2017; Stein et al., 2015).

Overall, the percentage of explained variance in this study is relatively modest in comparison with the percentages reported in the literature for the UTAUT model (around 70% for use intentions and 50% for actual use). Possible methodological explanations for the discrepancy could be (1) differences in the exact constructs included in the estimated models and the set of indicators that were used to measure these constructs, (2) the characteristics of the samples and settings, (3) the collection of computer-recorded usage data versus self-reported data, (4) the timing of data collection (with data on actual use being collected several months after self-reported use intentions), or (5) a publication bias. In addition, cross-sectional technology acceptance studies often differ with respect to the recency of the technology implementation, which may account in part for differences in the observed relationships and explained variance (Sabherwal, Jeyaraj, & Chowa, 2006).

Recent longitudinal and multi-level qualitative studies on technology acceptance and use (e.g., Burton-Jones & Gallivan, 2007; Jasperson et al., 2005) have also advocated for a segment-level approach by showing that implementation failures within organizations are most likely to occur when resistance is organized at the group level (Lapointe & Rivard, 2005). If technology resistance grows stronger over time and gets organized at a group or segment level, the so-called “hidden minefield” (Speier & Venkatesh, 2002) could easily become a battlefield, with a partial or complete withdrawal of the new technology as a possible outcome (Lapointe & Rivard, 2005). It is important to stress here that not all resistance is futile (see, for example, Meissonier & Houzé, 2010), because there can be valid reasons to resist a new technology, such as inadequate terms of use, lack of user input, or feelings of injustice in the workplace (e.g., Bagayogo et al., 2013; Martinko, Zmud, & Henry, 1996; Saleem, 1996). Finally, it should be noted that even though the theoretical or structural model that serves as the basis for segmentation may be context-specific (eg, studying technology acceptance versus resistance), the method put forward in this article can be applied to all types of situations (eg, private or company use and voluntary or mandatory use, see Bhattacherjee et al., 2017) as long as there is sufficient heterogeneity in the estimated (mental) models across users.

5.3 | Limitations and future research

The empirical study served as an illustration of the segment-wise approach to analyse technology acceptance models, hence statistical considerations in determining the number and profiling of segments were given priority over practical or managerial considerations. Precautions were taken to reduce common-method bias: (1) both subjective and objective data were collected, and in the survey (2) the scales of a number of measurement items were reversed, (3) the order of items and constructs was randomized, and (4) different scale formats were used. However, this does not completely rule out the presence of common-method bias. Also, the reliability of a number of well-established measurement scales was weak, making it arguably more difficult to detect significant effects for the concerned variables.

The reported results in this article are specific to the sample and context, which limits the generalizability of the findings. Even though the response rates of approximately 30% are comparable to other SFA technology acceptance studies, non-response may have biased the results. To check for potential biases, a comparison was therefore carried out between (1) early and late respondents to the survey and (2) respondents to the survey and all registered users. Concerning the latter comparison, the respondents to the survey seemed inclined to use the new technology more frequently. However, it is unlikely that this affected the validity of the segment-wise analyses of the TAM/ UTAUT models, because the sample exhibited sufficient variance in terms of attitudes, intentions, and actual use and substantial heterogeneity in the underlying TAM/ UTAUT model estimations to warrant the creation of separate segments. The reported segment sizes, however, may not be generalizable if employees belonging to the *Pockets of Likely Acceptance* segment were more likely to respond to the survey. In addition, larger samples may help uncover other meaningful (sub-)segments and may alleviate missing data issues, as for the estimation of the UTAUT model in the empirical illustration. This article hopefully incites new segmentation studies or re-analyses of existing technology acceptance data to enhance the generalizability, robustness, and comprehensiveness of the created segments and their profiles.

The relevance of the different factors for explaining technology acceptance and use may not only vary across segments, but also over time (see Kim & Malhotra, 2005). People's subjective evaluations of a new technology and their use of a new technology may change over time, especially when initial judgments were based on limited experience (Venkatesh et al., 2008). Although the bulk of technology acceptance research has focused on the adoption phase, the post-adoption phase (or "continued use") has attracted more attention recently (e.g., Ahearne, Srinivasan, & Weinstein, 2004; Ahuja & Thatcher, 2005; Bhattacherjee & Lin, 2015; Jasperson et al., 2005; Ortiz de Guinea & Markus, 2009; Venkatesh et al., 2008). Increasing experience with a new technology will enable users to "form more realistic and accurate expectations of IT usage" (Bhattacherjee & Premkumar, 2004, p. 240). Hence, in the post-adoption phase, subjective evaluations of the new technology, such as perceived usefulness, can be expected to correlate more strongly with the actual use of the technology (Bhattacherjee, 2001; Karahanna, Straub, & Chervany, 1999; Limayem & Cheung, 2008). Other IS scholars, however, have argued that the importance of technology-related factors for explaining intentions and behaviour diminishes with continued use, ie, relative to context-related or person-related factors, as behaviour becomes increasingly habitual (e.g., Kim, Malhotra, & Narasimham, 2005; Polites & Karahanna, 2013).

With increasing experience, it seems reasonable to expect that *Pockets of Likely Acceptance* will adjust their initial evaluations of the new technology downwards, as its newness will have worn off and their high expectations may not have been met entirely. *Pockets of Potential Resistance*, on the other hand, may have experienced the benefits of using the new technology (in particular when use is mandatory, as in Markus' (1983) study, for example) and are thus more likely to adjust their initial subjective evaluations of the new technology upwards. As a result, differences between the "technology acceptance model"-based segments concerning the subjective evaluations of the new technology are likely to be less pronounced in the post-adoption phase, with stated attitudes and intentions more closely reflecting the true quality and performance of the new technology rather than the segments' predispositions and expectancies.

In a similar vein, the degree of heterogeneity in technology acceptance model estimations may reduce over time, making a segment-wise approach less pertinent. In the empirical study, there were no significant differences between segments in terms of the "months of experience with the new SFA technology" variable (see the last row in Table 4), meaning that respondents from countries in which the technology was just launched and those from countries in which it had been launched several months earlier were proportionally distributed across segments. However, this does not mean that attitudes, intentions, and behaviour do not evolve over time, as evidenced by the significant correlation between "months of experience with the new SFA technology" and "use intentions" (r = .16, p = .009) as well as "actual use" (r = .41, p < .001). Thus, the longer employees had worked with the technology, the higher their use intentions and actual use. Segment dynamics, from pre-adoption to post-adoption and continued use, provide an interesting avenue for further research (cf. Bhattacherjee et al., 2017).

5.4 | Managerial implications

Facilitated by the increasing availability of data, segmentation strategies recognize that substantial similarities as well as differences between individuals exist and need to be taken into account when devising interventions to change people's attitudes, intentions, and behaviours (Steenkamp & Ter, 2002; Wind & Bell, 2007). To enable such interventions, segmentation studies in the context of technology acceptance and use need to address the following questions: (1) how many distinct segments are there?, (2) how do these segments think, feel, and behave? (3), what are the specific characteristics of people within these segments?, and (4) how can they be reached? (Gatignon & Robertson, 1991; Wind & Bell, 2007)? For each segment, management can then: (1) assess the likelihood of acceptance or resistance (and how this can change over time), (2) determine the key drivers and inhibitors, and (3) devise possible intervention strategies.

Segment profiles may not only be useful for facilitating technology implementations within companies, but could also be used for recruitment and selection purposes (see Agarwal & Prasad, 1999). In the context of a company's sales force, this is even more important because salespeople are generally more autonomous than their office-bound colleagues, which may make them less susceptible to pressure or influence from within the organization (Morgan & Inks, 2001). It has been argued that salespeople are a special breed, as they can be rather technophobic and self-willed by nature (e.g., Parthasarathy & Sohi, 1997; Schillewaert et al., 2005). In the empirical study, however, only the "Big Five" personality traits "openness to new experiences" and "neuroticism" were found to differ significantly across segments. In addition to assessing the person's sales skills and experience, these "Big Five" traits can be measured easily as part of standard recruitment and screening procedures.

The company featured in this study based their roll-out of the new SFA technology on country "profiles", starting in countries (such as the UK and The Netherlands) that they deemed easier to win over and then applied the "lessons learned" to tackle more difficult countries (such as France, Germany, and Belgium). However, the data reported in this article do not reveal a country bias in terms of the underlying structural technology acceptance models, as the respondents from the countries were proportionally distributed across segments (see Table 4). This is not to suggest that country (or culture) does not matter when it comes to the acceptance and use of new technologies. There were significant differences between the respondents from the 3 countries reported in Table 4 with regard to their scores on perceived usefulness, use intention, and actual use. Respondents in France were generally less positive or inclined to use the new technology than those in Italy (p = .019 for perceived usefulness, and p = .001 for actual use) and those in the UK (p = .009 for use intention, and p < .001 for actual use). These findings appear consistent with the company's phased roll-out strategy of the new SFA technology. In their qualitative comments to the survey (which were optional), respondents seemed generally appreciative of the new technology and only offered suggestions for improvements regarding specific functions and the new SFA technology's compatibility with other systems. However, a non-negligible number of them were cautious or even outright critical. The complaints of these employees need to be properly dealt with in order to prevent technology implementation failures (cf. Morgan & Inks, 2001; Parthasarathy & Sohi, 1997; Schillewaert et al., 2005), especially if these people start to organize and influence others.

In conclusion, a segment-level analysis of technology acceptance models can help uncover valuable and actionable insights, which may benefit researchers and practitioners alike. However, more research is needed to develop generalizable, robust, and comprehensive segment profiles for *Pockets of Likely Acceptance*, the *Pragmatist Herd*, and *Pockets of Potential Resistance* (or any other segment) before they can be put into action for screening, targeting, and intervention purposes in order to facilitate new technology implementations in organizations.

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ENDNOTES

[1] Computer-recorded data on the frequency of use were missing for 39 respondents to the survey.

[2] One respondent was removed due to numerous missing values and 4 respondents who were part of the IT staff implementing the technology were also removed. The remaining respondents (N = 260) were mostly sales specialists (49%), followed by sales managers (27%), consultants, marketers, and higher management. They were proportionally distributed across segments (Cramer's V = 148, P = .731).

[3] The pairwise deletion method was used for handling missing values (see, for example, Ringle et al., 2010).

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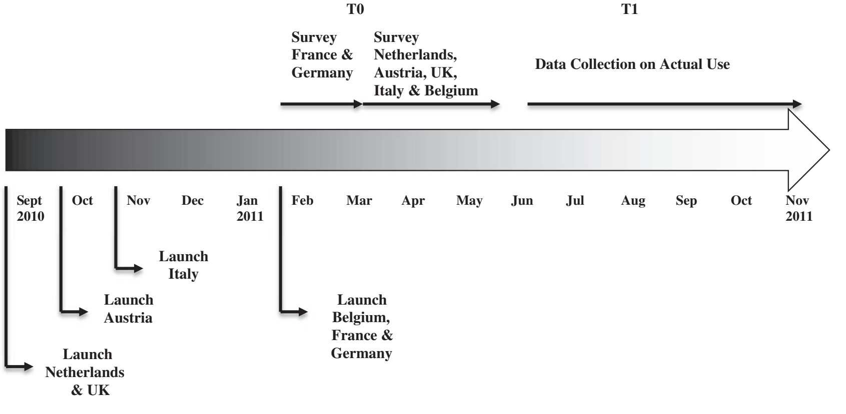
APPENDIX A

Timeline SFA Technology Launch and Administration of Surveys



APPENDIX B

Measures: Constructs, Items, and Reliability

Constructs	Items	Alpha	Source/Reference
Actual use	Computer-recorded number of times [X] was accessed over a 6-month period	-	Ahearne et al. (2004); Devaraj and Kohli (2003)
Technology-related factors			
Use intention	• I think that in the future I will use [X] frequently (1) —seldomly (5) (r) • I expect to use [X] barely (1)—intensively (5)	0.69	Davis (1989); Venkatesh and Bala (2008)

(Continues)

(Continued)

Constructs	Items	Alpha	Source/Reference
Attitude towards the technology	• My attitude towards the use of [X] can be described as positive (1)—negative (5) (r) • If asked to recommend [X] to others, I will do that enthusiastically (1)—reluctantly (5) (r) • Using [X] will be/ is boring (1)—fun (5) • Updating the information of my accounts in [X] will be/ is pleasant (1)—unpleasant (5)(r)	0.81	Agarwal and Prasad (1999); Davis et al. (1989); Davis, Bagozzi, and Warshaw (1992); Venkatesh and Bala (2008)
Perceived usefulness	• [X] will allow/ allows me to be more effective • [X] will allow/ allows me to be more efficient • [X] will make/ makes it easier to do my job • [X] will improve/ improves my job performance (5-point scale from 1 = not at all to 5 = very much)	0.96	Davis et al. (1989); Schillewaert et al. (2005); Venkatesh (2000)
Perceived ease of use	• For me, learning how to use [X] will be/ was difficult (1)—easy (5) • Working with [X] will be/ is simple (1)—hard (5) (r)	0.70	Davis et al. (1989); Venkatesh (2000)
Context-related factors			
Social influences	Please indicate the impact of the following factors that may have influenced your use of [X]: (1) Colleagues, (2) My manager, and (3) Top management (5-point scale from 1 = very negative impact to 5 = very positive impact)	0.73	Karahanna et al. (1999)
Facilitating conditions	Please indicate the impact of the following factors that may have influenced your use of [X]: (1) Training sessions and (2) My previous experience with similar systems. (5-point scale from 1 = very negative impact to 5 = very positive impact)	0.35	
Person-related factors			
Socio-demographics			
Gender	Single-item, 2-point scale with 0 = male and 1 = female	-	Karahanna et al. (1999); Venkatesh et al. (2003)
Age	Single-item, 9-point scale from 1 = under 25 to 9 = over 60	-	Venkatesh et al. (2003)
Education level	Single-item, 5-point scale from 1 = primary education to 5 = graduate/post-graduate level	-	Agarwal and Prasad (1999)
Tenure	Single-item, 6-point scale from 1 = less than 1 year to 6 = more than 20 years	-	Agarwal and Prasad (1999); Ahuja and Thatcher (2005)
Country	Single-item, 7-point scale with 1 = France, 2 = Germany, 3 = Austria, 4 = The Netherlands, 5 = UK, 6 = Italy, and 7 = Belgium	-	Leidner and Kayworth (2006)
Personality traits			
Openness to experience	• I see myself as someone who has an active imagination • I see myself as someone who is inventive (5-point scale from 1 = completely agree to 5 = completely disagree)	0.52	Costa and McCrae (1992); Rammstedt and John (2007)
Agreeableness	• I see myself as someone who is generally trusting	0.45	Costa and McCrae (1992); Rammstedt and John (2007)

(Continues)

(Continued)

Constructs	Items	Alpha	Source/Reference
	• I see myself as someone who is considerate and kind to almost everyone (5-point scale from 1 = completely agree to 5 = completely disagree)		
Neuroticism	• I see myself as someone who gets nervous easily • I see myself as someone who worries a lot (5-point scale from 1 = completely agree to 5 = completely disagree)	0.56	Costa and McCrae (1992); Rammstedt and John (2007)
Conscientiousness	• I see myself as someone who does a thorough job • I see myself as someone who perseveres until the task is finished (5-point scale from 1 = completely agree to 5 = completely disagree)	0.68	Costa and McCrae (1992); Rammstedt and John (2007)
Extraversion	• I see myself as someone who is sociable, outgoing • I see myself as someone who has an assertive personality (5-point scale from 1 = completely agree to 5 = completely disagree)	0.50	Costa and McCrae (1992); Rammstedt and John (2007)
Innovativeness in IT	• I normally do not adopt new software before other people have done the same (r) • I will not buy new software without trying it first (r) • In general, I am among the first in my circle of colleagues to try new software when it becomes available • If I hear that new software is available, I may consider buying it • Compared with my colleagues, I use a lot of different software (5-point scale from 1 = completely disagree to 5 = completely agree)	0.64	Agarwal and Prasad (1998); Leonard-Barton and Deschamps (1988); Schillewaert et al. (2005)
Actualized innovativeness	Which of the following products do you own or use on a regular basis? • Smartphone, Notebook, 3D Television, TV or movies on demand, MP3 Player, Tablet PC, Wireless Internet (at home), Social Media, Latest Generation Game Consoles, Flatscreen TV (index scale from 0 = low to 10 = high)	-	Van Rijnsoever and Donders (2009)
Cognitive styles			
Analytical—heuristic	• In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? • If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? • A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? (index scale from 0 = heuristic to 3 = analytical)	-	Frederick (2005)
Other variables			
Attended training session	Did you attend a training session for [X] (0 = no, 1 = yes)	-	Agarwal and Prasad (1999); Karahanna and Straub (1999)
Experience with technology	Constructed variable: number of months between date of launch and survey	-	-