Are You a Maverick? Towards a Segmentation of Collaboration Technology Users

by

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Are you a Maverick? Towards a Segmentation of Collaboration Technology Users

Research-in-Progress

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Abstract

Collaboration technologies are heavily used in organizations enabling employees to communicate, cooperate, and collaborate with each other. There exist much research investigating why different people are using different kinds of collaboration technologies, but some of the research results on technology acceptance are contradictious. A reason for these inconsistent results may be unobserved heterogeneity. Aiming to understand the heterogeneity, the presented research-in-progress discusses the examination of collaboration technology user segments. By applying the finite mixture partial least squares (FIMIX-PLS) approach, we aim to provide a differentiated picture of factors affecting individuals in their acceptance of collaboration technologies. Our preliminary results indicate that the aggregated model basing on the four identified segments provides more explanations than the global research model. Our overall research contributes to existing research, since we characterize different users groups and thus, improve interpretability of collaboration technology acceptance.

Keywords: Collaboration technology, segmentation, FIMIX-PLS

Introduction

In times of globalization and virtual as well as multi-cultural teams, effective and efficient collaboration plays an increasingly important role in many companies. To increase communication, coordination, and cooperation between employees, companies implement collaboration technologies to enhance individual and group performance (Kang et al., 2012). Collaboration technologies come in different forms, ranging from single mini-applications, like wikis or blogs, to large-scale integrated platforms, such as Microsoft SharePoint or IBM Connections. Despite the broad spectrum, the acceptance and use of collaboration technologies are *"not progressing as fast or as broadly as expected"* (Brown et al., 2010, p. 11). To achieve acceptance and continuous usage of collaboration technologies, they have to fit to individuals' tasks (Goodhue & Thompson 1995), characteristics, and preferences (Brown et al., 2010).

Only few years ago, organizations have implemented a pre-defined set of collaboration technologies to support their employees in collaborating with each other. Thereby, the decision of particular technologies has been made to meet the needs of the organization rather than the employees (Baskerville 2011). However, people are getting more and more tech-savvy and, thus, prefer to adapt their favorite technology to their tasks, problems, skills, and experiences (Ortbach et al. 2014). Consequently, a one-size-fits all strategy is no longer contemporary and companies as well as researchers are examining new, modern and flexible strategies to adapt the infrastructure of organizational information technologies (IT) to the needs and preferences of their employees. Bring-your-own-device (BOYD) respectively choose-your-own-device (COYD) initiatives are two famous examples of such strategies (Forrester 2012), but come with a set of issues. In particular, security issues and the high complexity of support are two main reasons why companies still refrain from adapting BYOD or CYOD (Ortbach et al. 2014). Another strategy balancing between the one-size-fits-all approach and BYOD or CYOD may be the identification of different user segments and the implementation of technologies adapted to these segments. While there exists a vast amount of research studying the preferences and factors influencing individuals' decision to adopt and use certain technologies, there are only few attempts to form segments of users to adapt information technologies to various needs and preferences. Factors directly impacting individuals' adoption and use of a certain technology such as social influence (e.g. Agarwal et al. 2009; Hsieh et al. 2010; Lou et al. 2000; Vodanovich et al. 2010), facilitating conditions (e.g. Brown et al. 2010; Hong et al. 2011; Sykes et al. 2009), or outcome expectations (e.g. Compeau and Higgins 1995; Kang et al. 2012; Wixom and Todd 2005) are intensively studied and examined in various contexts. In addition, there exists a vast amount of control variables that need to be considered, when interpreting the effects. Typical examples are individuals' demographics like age, gender, socio-economic status and education (e.g. Dimaggio et al. 2001; Hsieh et al. 2011; Sipior et al. 2010; Trauth et al. 2009; Wattal et al. 2010), their technology experience (e.g. Brown et al. 2010; Hargittai 2010; King and Teo 1996), and the organizational conditions like size and culture (e.g. Bajwa et al. 2008; Becker et al. 2012; Wattal et al. 2010).

Based on all the factors, established theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been examined, extended, supported and partially disproved multiple times (see Brown et al. 2010; Davis 1989; Venkatesh et al. 2003). In his research, Davis (1989) for example, observes a significant relation between perceived ease of use and usefulness of a technology. This relationship has been proved multiple times in various studies (e.g. Lou et al. 2000; Sipior et al. 2010). On the contrary, other researchers (e.g. Lewis et al. 2003; Nam et al. 2013) could not confirm this relationship. By providing additional examples of various results when applying the TAM, Becker et al. (2013) explain vividly reasons for partially contradictory observations. Although researchers *"routinely address observed heterogeneity by introducing moderators, a priori groupings, and contextual factors in their research models, they have not examined how unobserved heterogeneity may affect their findings"* (Becker et al. 2013, p. 665). Unobserved heterogeneity may result in Type I and Type II errors. To prevent both error types, a better approach may be considering the entire set of factors having impact on individuals' decision of technology adoption and use. Given the high dimensionality, the realization of such an approach would be very complex, if not even impossible. To understand the needs of individuals, the observation of various user groups – being as homogeneous as possible within the group and as heterogeneous as possible among different groups – may help to handle the high complexity of influencing factors. Thus, the segmentation of technology users can enable researchers to understand, how and why certain factors influence users' decision to adopt and use a technology and facilitate organizations to provide the optimal set of technologies for their employees. Moreover, being able to understand possible user segments and their individual needs might enable organizations to improve the adoption and usage of information technologies. Considering potential segments within the workforce, organizations can balance the tradeoff between standardizing their technology infrastructure and more modern, flexible concepts such as BYOD and CYOD (Baskerville 2011). Supporting the individual needs of the possible user segments will increase their overall satisfaction with and acceptance of the offered information technology (IT), and thus, might enable an effective usage of the technology (Burton-Jones and Grange 2013). Focusing on collaboration technologies as a particular type of information systems (IS) and the acceptance of IS in general, we aim to answer the following research question:

> What segments of collaboration technology users exist and how can these segments be characterized?

The remainder of this paper is structured as follows: The next section provides an overview of related work. Subsequently, the research method applied to identify our segments of collaboration technology users is presented. Then, we present some preliminary results and discuss our next steps in order to analyze and interpret the identified segment collaboration technology users. Since our research is ongoing, the final section briefly concludes the presented research with our future research steps and intended contributions.

Related Work

Since the emergence of personal computers, the Internet, and modern IT, many researchers of the IS field have observed individuals' adoption and use of these technologies. One of the most referenced theories explaining users' intention to use a technology is the Technology Acceptance Model (TAM) by Davis et al. (1989). In TAM, the decision of individuals to adopt a technology is modeled based on their perceptions with regard to the ease of technology use, its usefulness, and their attitude towards the technology. Since its publication, TAM has been often extended by various researchers. Venkatesh et al. (2003), for example, extend TAM by including constructs of further theories (e.g. Theory of Reasoned Action, Theory of Planned Behavior, Model of PC Utilization) resulting in the UTAUT model. Over time, TAM and UTAUT have been applied multiple times for explaining the adoption and use of various technologies in multiple settings (e.g. Bostrom et al. 2009; Brown et al. 2010; Sykes et al. 2009).

While there is much research on technology acceptance and use and its influencing factors, only few of them are taking the broad spectrum of various factors into account that have an impact on individuals' decision to accept and use a technology. Rather most studies focus on a subset of relevant factors in order to handle the high complexity. Researchers like Becker et al. (2012) and Prensky (2001) focus on discovering differences in the IT adoption and use between different generations. Such an age-related differentiation led to an often cited user segmentation discussed by Prensky (2001). Prensky (2001) differentiates technology users in "digital natives" (those who are grown up with modern technologies) and "digital immigrants" (being users that have to learn the usage of new technologies). While some researchers (e.g. Czaja and Sharit 1998; Glass 2007) observe significant differences between these generations of technology users, others recognize that a strict age-based separation is not feasible to predict technology acceptance and use. In particular, a classification of technology users based on their age has less empirical evidence, and thus researchers (e.g. Brown & Czerniewicz, 2010; Hargittai, 2010) call for more research *"to separate facts from appealing anecdotal distinctions"* (Becker et al., 2012, p. 388). Brown and Czerniewicz (2010), for example, demonstrate that experience in technology use has a higher impact than users' age. They also identify a new group called "digital strangers" being born in the same generation like digital natives, but lack experience and opportunities to use technology. There seems to be *"as much variation within the digital native generation as between the generations"* (Bennett et al., 2008, p. 779).

Another attempt of forming groups of technology users has its origins in the field of marketing research. Segmenting customers respectively users of products is common sense in the marketing area. In his book *Diffusion of Innovations*, Rogers (1983) discusses five types of technology adopters based on the timing of technology adoption: (1) the innovators, (2) the early adopters, (3) the early majority, (4) the late majority, and (5) the laggards (Mahajan et al. 1990). While this categorization of adopters is applied and considered by several researchers in both marketing (e.g. Mahajan et al. 1990) and IS research (e.g.

Stafford 2003), it purely considers individuals that are adopting and using a technology. Factors influencing individuals' decision to accept a certain technology are neglected in this categorization.

Focusing on the skill levels, the method of computer use, and requirements on training and support, Rockart and Flannery (1983) identify six various types of computer users based on an interview series: (1) non-programming users who purely access data stored on the computer, (2) command level end users who access data and perform simple inquiries, (3) end user programmers utilizing command and procedural languages for their information needs, (4) functional support personnel being sophisticated programmers that are able to support other users, (5) end user computing support personnel who aid by supporting other users and developing applications, and (6) data processing programmers having the highest level of skills. Later on, in a quantitative study, Schiffman et al. (1992) tested and confirmed the end user types. Thereby, the researchers considered further factors such as frequency and time of use, number of software applications, and number of business tasks. Schiffman et al. (1992) also introduce and test the users IT dependency – a new measure being relevant when studying end user types.

However, all the attempts to identify segments of technology users base on a pre-defined set of factors influencing their decision to adopt and use a technology. However, many factors being also relevant for an appropriate segmentation are neglected. Thus, Prensky (2001) purely focuses on users' age, Mahajan et al. (1990) and Stafford (2003) concentrate on technology adopting individuals and their timing of adoption, and Rockart and Flannery (1983) as well as Schiffman et al. (1992) consider only users having a certain level of IT dependency on their job. However, factors like gender, experience, facilitating conditions or social influencing factors were neglected by all the user segmentation attempts.

We are aware of only one work that also aims to segment users by considering multiple influencing factors and discovering a heterogeneity that cannot be observed when purely applying one of the existing theories such as TAM or UTAUT. Focusing on the Expectation Confirmation Theory (ECT), Halilovic and Cicic (2013) apply the finite mixture partial least squares (FIMIX-PLS) method to observe various user groups of an Integrated Accounting and Budgeting Software (IABS) and various products of Microsoft's office package. Therefore, the researchers collected data from 419 participants with regard to their satisfaction and IS usage continuance. The researchers identified two segments: The first segment is characterized based on the stronger relationship between confirmation and satisfaction, while in the second segment the usefulness is the stronger predictor of satisfaction than confirmation. However, a main limitation of the work of Halilovic and Cicic (2013) is the small sample size. Since it is suggested to accept only those segments that have a size larger the 10% (Ringle et al. 2010) of the total sample size, Halilovic and Cicic (2013) were only able to identify a limited amount of segments. By utilizing a larger sample size, more and yet undiscovered segments could be identified. In addition, Halilovic and Cicic (2013) focus their work on IABS and Microsoft's office products, while we attempt to segment users of collaboration technologies. When studying collaboration technologies, we expect to observe much more heterogeneity of various segments, because the class of collaboration technology bundles a broad set of various technologies having a similar purpose. Thus employees can, for example, choose between the "old-school" telephone and emails, or more modern technologies such as chats or micro-blogs to communicate with each other. On the contrary, Microsoft's office (or similar) products are not so diverse and today heavily used by different kinds of knowledge workers, resulting in Halilovic and Cicic (2013) were not able to identify segments differing in technology use. Our research also differs in the application of the underlying theory. The ECT is well established in IS research to assess the users continued usage of an IT. Nevertheless, as we intend to examine segments based on individuals' acceptance of a technology, it could be worth to conduct a study utilizing UTAUT as it specifically aims to evaluate the use and acceptance of a technology. Summed up, Halilovic and Cicic (2013) proposed an interesting approach and we argue to bring their research one step ahead by utilizing UTAUT and incorporating a larger sample.

Research Method

For the segmentation of collaboration technology users, we applied the UTAUT model of Venkatesh et al. (2003), since the model and the corresponding constructs and items are well-established in IS literature. We are focusing on the acceptance of collaboration technology. The continuous and effective use of collaboration technology is not the primary focus of this research. However, as acceptance is a pre-requisite, our research might also be of interest for the IS use research stream. Considering existing work in the IS acceptance research areas, many contradictious research results on the individuals acceptance of technology can be identified. A possible reason for these inconsistencies can be traced back to the fact that not all influencing factors of individuals are considered in existing research. As the spectrum of such influencing factors is highly diverse, it seems reasonable to focus only on a set of factors. However, in order to get consistent and holistic results the application of sub-sets is not reasonable. In an intensive literature study, we, therefore, aimed to identify all influencing factors. The resulting set of factors can be clustered within the following four dimensions: (1) individual characteristics (e.g. age, gender, socio-economic status, education, expectations etc.), (2) social factors (e.g. influences by peers, relatives, family and friends or the critical mass of users), (3) organizational factors (e.g. facilitating conditions, company size, culture), and (4) job-related characteristics (e.g. IT-dependency, task characteristics). As the UTAUT model already covers a broad spectrum of these factors, we decided to apply the UTAUT for the identification of user segments. In particular, three clusters of influencing factors are included in the UTAUT model: (1) individuals' expectations (effort and performance expectancy), (2) social factors, and (3) organizational factors (facilitating conditions). Another possible restriction of current acceptance and use studies is the lack of reporting the voluntariness of the technology use. In their work, Venkatesh et al. (2003) point out that the UTAUT model is moderated by the voluntariness of technology use. As the user segmentation aims to cover the main preferences of each segment and therefore, targets at fulfilling the needs and requirements of the users, the question of mandatory and voluntarily technology use could be alleviated. Instead, organizations will be enabled to provide an IT infrastructure appropriate for each segment and thus, as all users are probably satisfied with the IT, the discussions of usage voluntariness might be mitigated.

Considering its benefits and limitations, we decided to use the UTAUT model of Venkatesh et al. (2003) in order to identify the segments using the FIMIX-PLS approach. Thereby, we want to remember that our primary intention is the identification of undiscovered segments of collaboration technology users, and not the testing or re-evaluation of the already verified UTAUT model. Thus, as for example done by Halilovic and Cicic (2013), every well-established theory can be applied to identify user segments increasing the explanatory power of the underlying theory.

In consequence, we mainly adopted the instruments of the UTAUT model to our research context. Only the social influence construct has been slightly adapted by us. For measuring individuals' social influence, we extended the set of items by the items of peer influence (PI) and superior influence (SupI) as suggested by Brown et al. (2010). Combining the items of Venkatesh et al. (2003) and Brown et al. (2010), we used eight items measuring social influence. The items of all constructs (effort and performance expectancy, facilitating conditions, social influence, intention to use and use) were measured by a seven-point Likert-type scale. In addition, we also collected data regarding participants' **demographics** (age, gender, education, ethnicity, number of children, household income, and overall financial situation), their **experiences, preferences, and usage** of various collaboration technologies (e.g. email, instant messaging, wikis, social networks, shared calendaring, etc.), some **organizational characteristics** of participants' employers (organization size and sector), and the characterization of their daily **tasks** (task interdependence and IT dependency).

Before implementing the survey, seven academics checked the instruments with regard to design, wording, and structure. Based on the discussions, we made minor changes regarding the wording and order of questions and finally implemented the online survey. In a pilot test, we tested the survey by inviting employees of different companies from various sectors. In total, 131 employees of companies from the banking, telecommunication, chemical industry, and IT software development sector completed the survey. After screening the data, 107 responses can be assessed as valid and were used for pretesting the study. After analyzing the data, all constructs except of facilitating conditions showed a Cronbach's alpha value exceeding 0.7, demonstrating sufficient internal consistency (Hair et al. 2014). Considering the composite reliability being a more modern measure of the internal consistency, all constructs fulfill the requirements of the 0.7 threshold. Thus, we can conclude that the quality criterion of internal consistency is fulfilled. Furthermore, the quality criterion of convergent validity is fulfilled as all constructs have an average variance extracted (AVE) greater than 0.5. Finally, the measurement model was tested with regard to discriminant validity. As the Fornell-Larcker-Criterion is also fulfilled, we can conclude that the measurement model fulfills all necessary quality criteria. Assessing the structural model, all path coefficients are significant at least a 0.05 level except for the path coefficients between effort expectancy and intention to use as well as between facilitating conditions and use. A missing significance of these paths could be explained by the low sample size of the pilot study. Regarding the variance in users' intention to use, the constructs performance expectancy, effort expectancy, social influence, and facilitating conditions explain 55.3% whereas the use construct is explained to 56.5% by the combined effects of all exogenous latent variables.

Based on the feedback provided by some participants, we again made minor changes to the survey design. Finally, the survey included six constructs with in total 21 items influencing technology acceptance. After extensive efforts to convince companies to attend the survey, we realized high interest on the one hand, but issues related to the workers council on the other hand. Therefore, we decided to hire an international service provider for online surveys and panels to receive a large sample size as heterogeneous as possible to establish a set of segments. Thereby, the service provider has been instructed to select panelists that are working as knowledge workers. Moreover, we requested a sample which is highly heterogeneous with regard to the panelists' demographics (e.g. age, socio-economic status, education). The survey was distributed to more than 1,700 German employees of different organizations from various sectors.

Preliminary Results

Within two weeks, 1,673 participants completed the questionnaire. After screening the final set of answers, we eliminated 340 respondents as we assessed their responses as unreliable (i.e. due to survey completion by applying unlikely patterns like alternating between two points or constantly referring to one point). Since the service provider for online surveys invited the participants, we had no information enabling us to check the data for the response rate and nonresponse bias. The average age of the respondents is 42.6 years, ranging from 18 to 73 years, and 49.9% of the respondents were female. Before segmenting the participants based on their collaboration technology usage, we tested the measurement model for significance of indicator loadings, internal consistency, convergent and discriminant validity. As indicated in Table 1, all constructs exhibit satisfactory results (Urbach and Ahlemann 2010).

Table 1. Assessment of reflective measurement model

					Fornell-Larcker-Criterion					
Construct	Item	Outer Loadings	Mean	SD	EE	PE	SI	FC	I2U	USE
Effort Expectancy (EE) (CR=0.944; α=0.882; AVE=0.894)	EE1	0.935	5.053	1.331	**.946**					
	EE2	0.956	5.354	1.373						
Performance Expectancy (PE) (CR=0.935; α=0.896; AVE=0.828)	PE1	0.872	5.419	1.396	.534	**.910**				
	PE2	0.939	4.991	1.573						
	PE3	0.918	4.854	1.628						
Social Influence (SI) (CR=0.945; α=0.934; AVE=0.683)	PI1	0.783	4.392	1.693	.379	.611	**.826**			
	PI2	0.793	4.254	1.697						
	PI3	0.867	4.628	1.772						
	SupI1	0.824	4.833	1.852						
	SupI2	0.840	4.623	1.885						
	SI1	0.871	4.207	1.818						
	SI2	0.852	4.203	1.784						
	SI3	0.775	4.355	1.737						
Facilitating Conditions (FC) (CR=0.914; α=0.813; AVE=0.842)	FC1	0.914	4.686	1.612	.497	.474	.486	**.918**		
	FC2	0.921	4.948	1.511						
Intention to Use (I2U) (CR=0.976; α=0.967; AVE=0.909)	I2U1	0.926	5.258	1.527	.530	.630	.603	.545	**.953**	
	I2U2	0.961	5.384	1.521						
	I2U3	0.969	5.362	1.524						
	I2U4	0.958	5.332	1.537						
Use (USE) (CR=0.976; α=0.950; AVE=0.953)	Use1	0.975	4.569	1.459	.445	.596	.592	.471	.715	**.976**
	Use2	0.977	4.567	1.488						

CR: Composite Reliability: α: Cronbach's alpha; AVE: Average Variance Extracted; SD: Standard Deviation

Regarding the structural model, all path coefficients within the UTAUT model are significant at a 0.001 level. In addition, the constructs performance expectancy, effort expectancy, social influence, and facilitating conditions explain 53.9% of the variance in users' intention to use collaboration technologies. This explanatory power can be perceived as moderate (Hair et al. 2014). 51.9% of the variance of the use construct is explained by the combined effects of all exogenous latent variables. Figure 1 provides an overview on the structural model based on the data of all considered participants. In the following, for the comparison of the various segments we refer to this model as the global model.

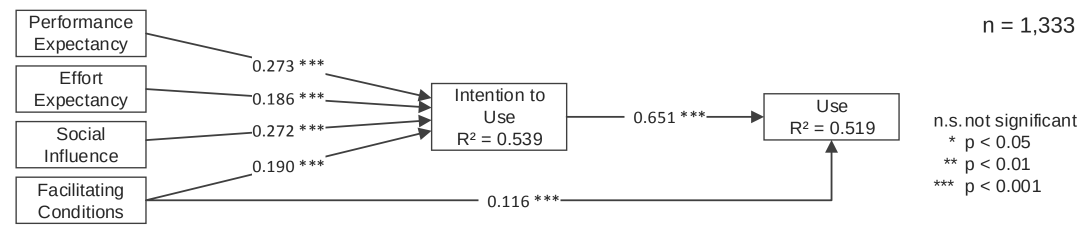

Figure 1. Research model (adapted from Venkatesh et al. 2003)

To identify appropriate segments of collaboration technology users, we applied the FIMIX-PLS approach as presented by Ringle et al. (2010). Therefore, the FIMIX-PLS algorithm uses the scores of latent variables in the inner path model as input. As suggested by Ringle et al. (2010), we started to identify the appropriate number of segments by running the FIMIX-PLS algorithm beginning with a two-segment model. Following, we increased the number of segments successively. For each number of segments, we run the FIMIX-PLS algorithm with ten iterations by adapting the according settings in SmartPLS version 3.2.0 (Ringle et al. 2015). We stopped the analyses at a five-segment model. Thus, for the identification of the segments, we considered the relevant evaluation criteria up to the four-segment model.

Table 2. FIMIX-PLS evaluation criteria and relative segment sizes

#	Akaike's Information Criterion (AIC)	Bayesian Information Criterion (BIC)	Consistent AIC (CAIC)	Normed Entropy Statistic (EN)	Relative Segment Sizes π_S					
					S=1	S=2	S=3	S=4	S=5	Sum
2	5,372	5,460	5,477	0.291	0.745	0.255				1.00
3	5,279	5,414	5,440	0.395	0.156	0.245	0.599			1.00
4	5,217	5,399	5,433	0.386	0.112	0.585	0.141	0.162		1.00
5	5,201	5,430	5,474	0.347	0.134	0.201	0.426	0.143	0.096	1.00

As indicated in Table 2, all relevant information criteria (AIC, BIC, and CAIC) are slightly decreasing beginning with the two-segment model. On the contrary, the normed entropy statistics (EN) increases with an increasing amount of segments. Ringle et al. (2010) suggest a selection of the segment number, where AIC, BIC and CAIC are minimal and the normed entropy statistic has a maximum value. Although the five-segment model has the lowest fit indices, we neglected this model, because the segment size of the fifth segment falls short the suggested 10% threshold (Ringle et al. 2010).

Table 3. Preliminary results of segment-specific estimation of PLS path model

	S=1	S=2	S=3	S=4	Global	R^2_w	Delta
R^2_S (Intention to Use)	0.380	0.844	0.967	.0697	0.539	0.786	0.247
R^2_S (Use)	0.442	0.722	0.950	0.421	0.519	0.674	0.155
Relative segment size (π_S)	0.112	0.585	0.141	0.162			
R^2_S explained variance in latent segment models, R^2_w weighted explained variance based on latent segment models							

As the EN of the four-segment and three-segment models are very similar, we decided to select the four-segment model as it has the lowest fit indices (AIC, BIC, and CAIC). In a next step, we divided our entire data set into four sets of data – representing the identified segments computed by the FIMIX-PLS algorithm. These data sets served as input for a segment-specific path model analysis of both, inner and outer models (Rigdon et al. 2010). We are currently in the ex post analysis (step 3 of the FIMIX-PLS analysis as described by Ringle et al. (2010)). Table 3 summarizes some preliminary PLS model results for the global model and the four latent segments.

When only considering the R^2 values of the constructs, some heterogeneity between the four models becomes obvious. First of all, the weighted explained variance of the intention to use construct (R^2 = 78.6%) based on the four latent segments is 24.7% higher than the explained variance in the global model. Similarly, the weighted explained variance of the use construct is 15.5% higher than in the global model. Thus, by considering various segments of collaboration technology users, the UTAUT model has a high explanatory power. This increase of explained variance is a first important result and supports our assumption that there is an undiscovered heterogeneity between various groups of (collaboration) technology users. Aiming to identify the differences between the segments, we separately run the PLS algorithm for the four segments. Figure 2 depicts the results for each segment.

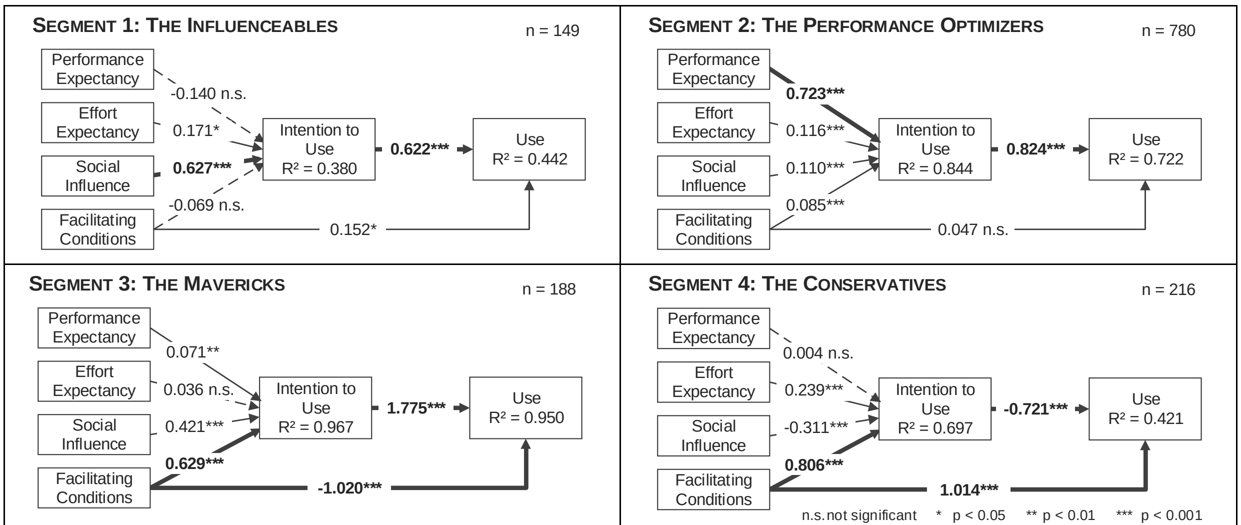

Figure 2. Four segments of collaboration technology users

Our first segment shows a strong path coefficient of the social influence on the intention to use. Consequently, we can conclude that users of the first segment are strongly influenced by the opinions of their relatives, peers, superiors and friends with respected to their intention to use a collaboration technology. Thus, we labeled the first segment the "*Influenceables*". In contrast to this, the users of the second segment are strongly influenced by their performance expectancy of the collaboration technology. The *"Performance Optimizers"* will most likely intend to use a collaboration technology if they expect an increased performance from using it. The facilitating conditions have a strong effect on the intention to use of the users from both, the third and the fourth segment. However, while in the third segment the mere provision of the technology does not lead to its usage, participants of the fourth segment use those technologies that are provided by the organization although the might not intent to use it. Since the users of the third segment only use those technology that they want to use (high intention to use leads to use), we named this segment the *"Mavericks"*. On the contrary, in the fourth segment individuals use the provided technology although their intention is low (negative effect between intention and use). Since the participants of this segment follow the organization's policies, we named the segment the *"Conservatives"*.

To complete our analysis, in the next steps we will test the segment-specific models with regard to its reliability and validity, before evaluating goodness-of-fit measures. Following, we will uncover explanatory variables by an ex post analysis as described by Rigdon et al. (2010). The explanatory variables enable a characterization of our segments. As support for this step, Becker et al. (2013) suggest to apply statistical techniques like discriminant analysis, exhaustive CHi-squared Automatic Interaction Detection (CHAID), or contingency tables in order to test various variables for their ability to explain differences in the segments.

Conclusion

This research-in-progress presents our ongoing study to identify and investigate so far undiscovered segments in users' collaboration technology adoption and use behavior. Using the UTAUT model and applying a FIMIX-PLS approach, we identified four segments in our survey-based collected data on the acceptance of collaboration technologies. In contrast to existing research, our approach is using a well-established theory on the acceptance and use of IT, the analysis is built on a large sample size, and we are considering multiple factors (e.g. social influence, facilitating conditions, outcome expectations, or demographics) influencing the acceptance behavior. While the analysis is still work in progress, our preliminary results are promising. We were able to identify a first set of four segments of users' collaboration technology acceptance behavior: Influenceables, Performance Optimizers, Mavericks, and Conservatives. Our analysis reveals that the explanatory power of the UTAUT model is higher when considering the four segments separately rather than in a global model. The identified segments show a high heterogeneity among each other when considering the path coefficients of the UTAUT model. The Mavericks, for example, only use the technology they want to use, in contrast to this, the Conservatives seem to follow the policies by the company. At the moment we are conducting a detailed analysis of the four segments to discover the differences between the user groups incorporating not only the constructs and items of the UTAUT model, but also the additional factors examined by us.

Although our research follows the guidelines for conducting a FIMIX-PLS approach (Becker et al. 2013), there are some limitations which need to be discussed. For the data collection, we used a service provider for online surveys and panels. In doing so, we were not able to fully control the participant sampling, and thus could not control for a non-response bias. However, the large sample size of the data due to the panel collection has a positive effect on the results of our segmentation approach. As outlined, we also conducted a pilot study where we purposefully sampled the participants of various companies. As the assessment of the measurement and structural model received by the panel data reflect the results by the pilot study, we can conclude that our user segments have an appropriate confidence level and are independent from the data collection method. As we are focusing on collaboration technologies in our study, further research is required to facilitate a generalization of our findings for all technology acceptance behaviors. However, as collaboration technologies play a vital role in most organizations, it is important to understand how success and performance increase due to the provision of proper collaboration technologies for different user segments.

Summed up, we propose a novel way on how to investigate the users' acceptance of collaboration technologies. Applying our segments, researchers and practitioners can built on our suggestions and results to investigate which factors have an influence on users' decision to accept and moreover to adopt and use a certain technology. Thereby, researchers will be able to interpret their research results and possible inconsistencies to others research. In addition, further research on technology acceptance can be done segment-specific decreasing the complexity of influencing factors that need to be considered. From practitioners perspective, managerial implications can be derived based on the identified segments and existing IS literature. Thus, managers will be facilitated to map the needs of employees regarding collaboration technologies to their existing IT infrastructure. By applying the managerial implications based on different collaboration technology user segments, companies will be able to balance their IT strategy between one-size-fit-all standardization solutions and individualization strategies such as bring-your-own-device (BYOD) or choose-your-own-device (CYOD). Consequently, organizations will be facilitated to handle high complexity of the IT infrastructure and security issues while providing their employees the IT they prefer to work with.

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