

5-15-2012

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DO WE FULLY UNDERSTAND THE CRITICAL SUCCESS FACTORS OF EMPLOYEE PORTAL UTILITARIANISM? - UNCOVERING AND ACCOUNTING FOR UNOBSERVED HETEROGENEITY

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Abstract

Employee portals are collaborative information systems that are utilized by many companies to improve information exchange, communication, and employee collaboration, as well as to better support their business processes. Although some studies investigate single aspects of portal success, the critical success factors of how employee portals help their users become more productive have to date not been fully explored. To understand the antecedents of realizing employee performance gains through employee portals, we propose and validate a model of factors based on the human-computer interaction literature, particularly to better understand heterogeneity. Accordingly, we apply the finite mixture partial least squares (FIMIX-PLS) approach to uncover different segments of employee portal users and thereby provide a differentiated and more complete segment-specific picture of antecedents of employee portal utilitarianism. Our analysis indicates that the aggregate global model hides the existence of meaningful system user segments that are more homogenous in the productivity drivers. While some users are primarily concerned with ergonomicity, others users' productivity is the result of functionality. The future research steps we outline include the finding of exploratory variables that characterize different user groups and therefore further improve interpretability.

Keywords: Employee Portals, Utilitarian Value, Human-Computer Interaction, FIMIX-PLS.

1 Introduction

Given the importance of employee productivity and its established relationships with higher pay, self-esteem, personal well-being, and corporate success, understanding how information systems (IS) can help people become more efficient and/or effective is a key concern in IS research. One such organizational information system, employee portal (EP), which has gained considerable popularity in the past few years, refers to a specific type of enterprise portal that seeks to provide employees with timely and relevant information and collaborative functionalities with which to perform their duties and make efficient business decisions (Benbya, 2004). Even though EPs have become widespread (Forrester, 2006), we do not fully understand the critical success factors that help EPs make their users more productive. Most of the few existing studies investigate single aspects of portal success. Sugianto et al. (2007) as well as Tojib et al. (2008) propose using the B2EPUS (business-to-employee portal user satisfaction) model to measure user satisfaction with EPs; this goes back to the work of Doll and Torkzadeh (1988). Bin Masrek (2007) proposes another approach to assessing user satisfaction with campus portals, based on a subset of the IS success model (DeLone and McLean, 2003). Focusing on the user-perceived service quality of web portals, Yang et al. (2005) developed and validated an instrument based on different conceptual models in the areas of IS and technology adoption. Based on the technology acceptance model (TAM) (Davis, 1989), de Carvalho et al. (2008) analyzed the effects of technological and organizational features on intranet and portal use. Both aiming at comprehensively examining the success of EPs, the study of Urbach et al. (2010) builds on the IS success model, while the approach of Mohan and Urbach (2011) is founded on theoretical behavioral science concepts. While user-oriented critical success factor models are relatively scarce in EP-specific literature, fundamental behavioral and technical theoretical models of the theory of planned behavior (TPB) (Ajzen, 1991) and TAM help fill this gap. Therefore, our first research objective is to develop and validate a comprehensive and – at the same time – parsimonious model that integrates the different success factors for explaining employee portal utilitarianism.

According to TPB, an individual's intention to use or not use a system depends on three beliefs: a) attitude towards using the system, b) subjective norms, and c) perceived behavioral control. The literature has constantly found that perception of usefulness (utility) is the most prominent of TPB factors (Zhang and Na Li, 2005). Usefulness/Utility, which refers to the functions provided by an information technology that supports a user's task or goals, is an important concern in IS research, because users will not use or interact with a system if it does not provide useful functions. Besides usefulness, another key concept in IS research is ease of use (EOU), which indicates how difficult or complex a user considers a system. Davis (1989) has integrated usefulness and ease of use in the technology acceptance model (TAM). Many technology acceptance studies based on TAM and using structural equation modeling techniques have found that perceived system usefulness is the dominant factor, and that perceived EOU is a significant secondary success factor with varying correlation strengths. This inconsistency might be because of the studies' restrictive assumption that the data originate from a *single homogenous population* (i.e. that the global model fully represents all observations) (Hahn et al., 2002; Ringle et al., 2010a). However, various psychological needs-based theories (e.g., Murray's theory of psychogenic needs (Murray, 1938)) state that people have different values, needs, perceptions, and desires and therefore behave differently. Consequently, assuming that the population is in fact heterogeneous, treating it as homogenous would lead to seriously distorted results (e.g., Muthén 1989; Ringle et al. 2009). Therefore, our second research objective is to examine whether uncovering individual homogenous segments in the data might help improve model fit, predictability and interpretability of results.

Analysis of population homogeneity, conducted mostly through segmenting, is most popular in the marketing literature; studies often acknowledge that truly homogenous segments do not exist (Sarstedt et al., 2009). In IS research, one prominent example is the Unified Theory of Acceptance and Use of Technology (UTAUT) of Venkatesh et al. (2003). In their model, they use the a priori variables age and

gender to study population heterogeneity. However, true distribution heterogeneity is never known a priori (Hahn et al., 2002) because there are two types of heterogeneity that could affect data: observed heterogeneity and unobserved heterogeneity (Vinzi et al., 2008). The first refers to the case of a priori existing segments developed by a researcher based on well-known observable variables (e.g., geographic or demographic) while, with the latter, no information exists on the number of segments and their composition. As Ringle (2006) points out, developing segments based on a priori information has serious limitations. For example, there is often only incomplete or no substantive theory regarding the variables that cause heterogeneity. Furthermore, observable characteristics such as age, gender, and usage frequency do not adequately capture heterogeneity. Therefore, in our study, we seek to uncover the *unobserved* heterogeneity in data. This implies identifying segments of EP users (a priori unknown) with similar values, needs, desires, and/or characteristics. Knowing the existence of such a priori hidden/unobserved user segments can potentially provide researchers and practitioners with a *new* understanding of 1) what specific user segments experience high productivity gains through EP use, and 2) how the importance of various critical success factors differ for different EP user segments. This paper presents the results of our initial analysis and gives an outlook on the future research activities part of this research study in progress.

The remainder of the paper is organized as follows: Section 2 discusses FIMIX-PLS, the technique used to uncover the unobserved heterogeneity and the underlying methodology. In Section 3, we present a concise overview of the research model and the data collected. In Section 4, we analyze the data and discuss the results. In Sections 5, we present our study's implications and outline the next research steps.

2 Uncovering Heterogeneity in Data with FIMIX-PLS

Since the 1980s, the use of structural equation models to analyze cause-effect relationships between latent variables has become the quasi-standard in management research (Ringle et al., 2010a). Among the popular statistical techniques for estimating causal models, the component-based structural equation modeling (SEM) technique partial least square (PLS) has recently gained widespread acknowledgement, especially in customer research and IS research (Henseler et al., 2009; Hulland, 1999; Urbach and Ahlemann, 2010). Some often cited advantages of PLS over covariance-based SEM are, among others, the ability to work with small samples, non-normally distributed data, complex models with a large number of variables and parameters to be estimated, models that incorporate formative measures, and samples in which observations are not truly independent from one another (Sarstedt, 2008). However, when working with path modeling SEM methodology, a fundamental problem arises when forming decisive interpretations when the underlying data is heterogeneous. PLS path modeling (PLS-PM) traditionally and often unrealistically assumes, without adequate justification, that individuals in a data set are homogeneous (Muthén, 1989), i.e. a single unique model estimated on the aggregate data set can optimally represent all individuals, despite varying perceptions and evaluations of latent constructs (Ansari et al., 2000). As a result, treating heterogeneous data samples as if they were homogeneous leads to inappropriate PLS results and flawed conclusions, as demonstrated, among others, by Muthén (1989), Jedidi et al. (1997), Ringle et al. (2010a), Sarstedt et al. (2009), and Hahn et al. (2002).

To solve this problem, different latent class (or segment) detection approaches specifically suited to PLS have been proposed to conduct response-based segmentation, for example, decision tree-like structure approach via PATHMOX (Sánchez and Aluja, 2006), distance-based approaches via PLS-TPM (Esposito Vinzi et al., 2007), REBUS-PLS (Trinchera et al., 2008), FPLS-LCD (Romano, 2007), PLS genetic algorithm segmentation (Ringle and Schlittgen, 2007), and FIMIX-PLS (Hahn et al., 2002). According to a review conducted by Sarstedt (2008), finite mixture partial least squares (FIMIX-PLS) is a key approach, developed by Hahn et al. (2002) and taken further by Ringle (2006) as well as Ringle et al. (2010b) to segment data in the PLS-PM framework. FIMIX-PLS complements the strengths of the PLS method with those of the maximum likelihood estimation when extracting

segments from the data set. It allows data classification based on the heterogeneity of inner path model estimates (Ringle et al., 2010a). FIMIX-PLS assumes that data stems from a source with several subpopulations or segments (McLachlan and Peel, 2000). Each segment is therefore modeled separately, and the overall population is a mixture of these subpopulations (Sarstedt, 2008). The use of the finite mixture methodology is appropriate here because, similar to conditions in most social sciences, in this study, substantive theory supports the structural equation model (see the next section), a priori segmentation is unfeasible, and theory suggests that data are heterogeneous (Jedidi et al., 1997). Ringle et al. (2010a) propose a systematic approach to conduct FIMIX-PLS analysis; this serves as a guideline for our research (see Figure 1).

In FIMIX-PLS Step 1, a path model is estimated using the basic PLS algorithm on the manifest variables in the outer measurement models. In Step 2, the resulting latent variable scores in the inner path model are used to run the FIMIX-PLS algorithm (for a detailed formal description of the algorithm, see Rigdon et al. (2010)). FIMIX-PLS captures the heterogeneity concentrated in the estimated relationships between the latent variables and calculates the probabilities of a particular observation belonging to a specific segment. The objective is to ensure that each observation fits into a predetermined number of segments (S). When identifying the appropriate number of heterogeneous segments characterizing the data, we precede in an exploratory manner. We successively increase the number of segments in a model ($S = 2, S = 3, \dots S = n$) and compare the models' FIMIX-PLS results based on specific quality/fit criteria to find the optimally segmented solution. This exploratory method is necessary because the number of segments is not known a priori when applying FIMIX-PLS, and there is no statistically satisfactory solution for this analytical procedure (Wedel and Kamakura, 2000).

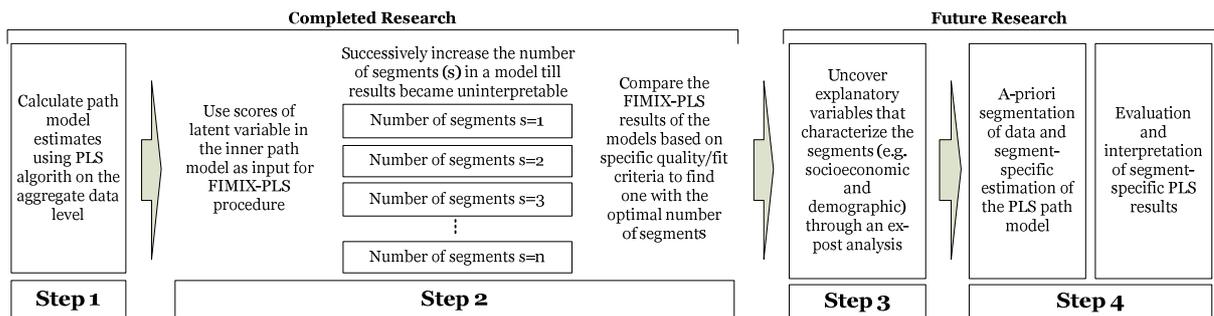


Figure 1. Systematic Application of FIMIX-PLS

Identifying the correct number of segments is a critical issue, because misspecification can result in an over-segmentation or under-segmentation, thus leading to flawed managerial decisions (Sarstedt et al., 2011). One useful indicator to help one decide when to stop the analysis of additional number of segment classes is segment size (ρ_s). This is because, after a certain point, an additional segment becomes very small and fails to explain any substantial heterogeneity in the data (Esposito Vinzi et al., 2007). When deciding on the optimal number of segments in a model, researchers resort to comparing estimates of different segment solutions, using heuristic goodness-of-fit measures (McLachlan and Peel, 2000), such as Akaike's (1974) information criterion (AIC_s), consistent AIC ($CAIC_s$) (Bozdogan, 1987), or Bayesian information criterion (BIC_s) (Schwarz, 1978). These heuristics integrate a penalty term for over-parameterization when calculating a model's goodness-of-fit. The use of these criteria for model selection is one of FIMIX-PLS's most important advantages, since other approaches to response-based segmentation do not provide any model selection guidelines (Sarstedt, 2008). When comparing models with different numbers of segments, one should pick one that minimizes the information criterion's value (Ringle et al., 2010a). Sarstedt et al. (2011) go further and suggest, based upon their simulation results, that a joint consideration of AIC and CAIC is most promising. However, even though the above-mentioned criterion provides researchers with reliable guidelines to evaluate segmentation quality, they do not ensure that the identified segments are sufficiently separable in the solution, i.e. that each segment is conceptually different and the latent variables are interrelated

differently in each segment (Ringle et al., 2010a). Regarding this issue, the normed entropy statistics (EN_s) classification criterion is used to reveal the most appropriate number of latent segments for clear-cut segmentation (Wedel and Kamakura, 2000). EN values range between 0 and 1. Generally, a model with an EN value of more than 0.5 is considered to represent unambiguous segmentation (Ringle et al., 2010a).

In Steps 3 and 4, which are part of the future research and are explained in the last section, explanatory variables (e.g., socioeconomic and demographic) are uncovered through an ex post analysis. These variables explain and provide a logical interpretation of the segmentation.

3 Model and Data

Since this study's primary goal is to uncover different EP user segments and thereby provide a differentiated and more complete segment-specific picture of antecedents of EP utilitarianism, we only provide a concise overview of the underlying model in this section.

An EP's usefulness or **Utilitarian Value (UV)** is reflected in the perceived outcome generated through its use, originating in an individual's mind through cognitive mechanisms relating to goal attainment. Marketing researchers have termed this task-related outcome utilitarian value, which seeks to provide instrumental value to the user, such as increased efficiency and effectiveness (Goodhue and Thompson, 1995). The effort to understand the antecedents of realizing employee performance gains through EPs is undertaken by proposing and testing a model of factors (see Figure 2) based on the human-computer interaction literature. We begin by developing an understanding of how EP perceived usefulness, specifically quality of collaborative support, leads to employee work-related benefits. We then add to the model concepts rooted in cognitive load theory (CLT) (Sweller, 1988) to incorporate the effect of aligning users' system interactions to their mental abilities, with the goal of reducing cognitive overload during these interactions.

Collaboration usefulness (CU): In light of globalization and the outsourcing of organizational activities, the workforce has become increasingly mobile. In such a scenario, an EP's most important functionality relates to supporting communication and connecting individuals within and between functions and divisions (Ryu et al., 2005) effectively and economically. Putting it simply, e-collaboration and collaborative functionalities of EPs helps bring geographically dispersed individuals together for virtual meetings across great distances to engage in distributed asynchronous interaction (e.g. e-mail, discussion forum), distributed synchronous interaction (e.g. videoconferences, shared screens), face to face interaction (e.g. group decision support systems), asynchronous interaction (e.g. project management) (Bafoutsou, 2002; Bullen and Bennett, 1991). This helps employees save much time and costs, decreases travel requirements (Kock and McQueen, 1997), and fosters faster and better decision-making, thus improving their productivity quality, efficiency, and performance (Cooper, 2003; McLeod and Liker, 1992).

H1: Collaboration usefulness will be positively associated with Utilitarian Value (UV).

Ergonomics (EG): The research stream on ergonomics, an aspect of engineering psychology, is concerned with adapting equipment and the environment to people, based on their psychological capacities and limitations, with the objective of reducing cognitive load and improving overall performance. The term cognitive load, as suggested by CLT, is used to describe the amount of work imposed on a person's working memory and is shown to negatively effect individual performance. In line with CLT's intrinsic and extraneous cognitive load concepts, cognitive load regarding EP can occur because a) an EP is not compatible with the user's skills and knowledge, thereby requiring the user to exert much mental effort to correctly use the EP, and b) an EP's bad visual look and feel increases comprehension time and reduces the user's ability to process information, thereby increasing cognitive burden and overload. The reduction of cognitive load is particularly relevant to collaboration activities, as individuals in collaborative environments are exposed to the task of rapidly collecting, filtering, sharing, and processing large quantities of information conveyed over multiple interactive

audio-visual channels (McQueen, 1992), putting tremendous pressure on a person’s limited memory resources, resulting in information overload. Furthermore, lack of ergonomicity can cause unpredictable and uncontrollable interruptions in cognitive information collection and interpretation processes. This can cause people to forget, cause work accidents, and make mistakes, reducing their efficiency and performance (Cellier and Eyrolle, 1992; Gillie and Broadbent, 1989; McFarlane and Latorella, 2002). For specific users, cognitive load has also been observed to cause a number of psychological problems, such as a general lack of perspective, stress, confusion, strain (Schick et al., 1990), disorientation, demotivation (Baldacchino et al., 2002), dissatisfaction (Jacoby, 1984), and over-confidence (O'Reilly Iii, 1980) which adversely affects their work performance.

H2 and H3: EP ergonomicity is positively associated with CU and UV.

Facilitating conditions (FC): Facilitating conditions are objective factors that make EP use easy (or difficult). Facilitating conditions has its conceptual foundations in the work of Triandis (1980) and the TPB construct perceived behavioral control (Ajzen, 1991). In our research, the desirable external facilitating conditions refer to the support services offered by organizational institutions such as the IT department in the form of guidance in the correct usage and customization of EP to suit users’ cognitive needs. Competent, reliable, and fast support that takes into consideration users needs can help the user to customizes a EP to match his or her individual cognitive capabilities i.e. make the system ergonomic. The more high-quality support a user can get when he or she needs it to solve EP technical and customization issues, the more ergonomic the EP will be perceived to be, the more confidence the user will have in successful usage, and the more inclined he or she will be to use the full breadth of EP functionality (Ajzen, 1991). Facilitating conditions have been shown to directly elevate the usefulness of information systems (e.g. (Jiang et al., 2000; Jong-Ae, 2006; Lu et al., 2008)). Taking users step by step through techniques such as tutorials, lectures, seminars, courses, and computer-aided instruction on how to use the various EP applications in a manner that enables them to make the best of the underlying functions prevents or mitigates trial-and-error learning behavior and is expected to increase the usefulness of an EP’s collaboration functionalities.

H4, H5, and H6: Facilitating conditions is positively associated with EG, CU, and UV.

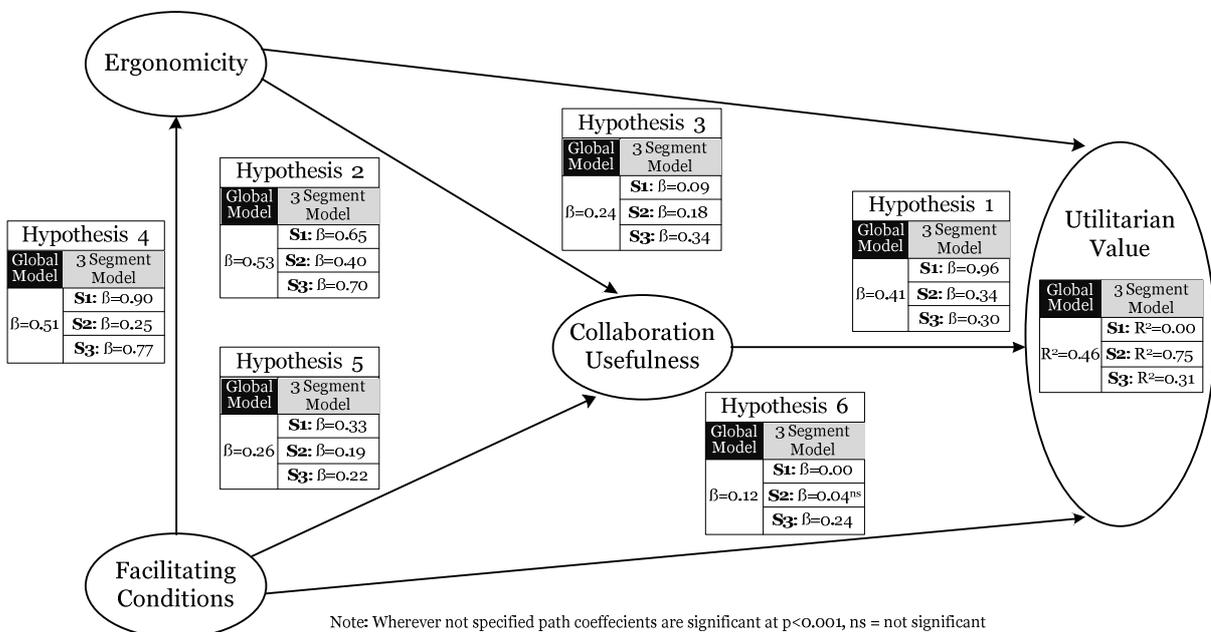


Figure 2. FIMIX-PLS Results of Three Latent Segments

4 Application of FIMIX-PLS: Data Analysis and Results

The PLS path model analysis draws on data collected via an online survey, developed following Straub's (1989) recommendations, from 19 multinational firms of different industries. We acquired these companies' participation by inviting them and other companies to participate in an international benchmarking study. We provided each of the companies with a hyperlink to the online end-user survey, asking them to distribute it via e-mail to all or a subset of their employee portal's users. In order to minimize bias caused by differences in addressing the survey participants, we also provided the companies' coordinating persons with invitation templates. In these templates, as well as on the start page of the online survey, we emphasized that all data would be handled with the strictest confidentiality and that the identity of the respondent could not be inferred. We did this, as well as taking other steps, to achieve the best possible response rate. The invitations to the employee portal users were sent out at the beginning of the survey period. In some companies, participation was also advertized by other internal announcements. Two weeks later, we asked the companies' contact persons to send their employees a reminder. All the companies again requested their employees to participate. After an overall survey period of six weeks, we closed the online survey. We received more than 10,000 responses, leading to an average response rate of 36.7 % across all participating organizations. After rigorous data cleansing (i.e. considering only complete data sets), we considered 5,783 user responses for our analysis.

Even though this is not this paper's primary aim, the existence of reliable and valid measures is a prerequisite for delivering meaningful solutions and is therefore discussed here. The research model and propositions were tested and the scales' psychometric properties were assessed with the software SmartPLS (version 2.0 M3) (Ringle et al., 2005). We used Cronbach's Alpha (CA) reliability estimates to measure internal consistency reliability. In this study, each construct's CA is greater than 0.63, which indicates an acceptable reliability for all constructs in our model. Additionally, composite reliability (CR) values for all constructs are higher than .84 and, thus, above the recommended minimum of 0.7. Convergent validity is demonstrated, as a) the average variance extracted (AVE) values for all constructs were higher than the suggested threshold value of 0.5, and b) all item loadings were well above the 0.7 guideline and statistically significant at the .001 level. Evidence of discriminant validity could be found, since a) the square root of all AVEs was larger than the inter-construct correlations, and b) all construct indicators loaded on their corresponding construct more strongly than on other constructs (Chin, 1998), and the cross-loading differences were generally higher than the suggested threshold of 0.1.

S	lnL	AIC	BIC	CAIC	EM	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	Sum
2	-21134.29	42306.58	42432.57	42432.57	.45	.31	.69					1.00
3	-19484.51	39027.01	39219.32	39219.32	.59	.10	.53	.37				1.00
4	-20214.59	40507.18	40765.8	40765.81	.57	.47	.36	.10	.07			1.00
5	-21301.53	42701.05	43025.98	43025.99	.51	.44	.27	.14	.09	.06		1.00
6	-22861.44	45840.89	46232.13	46232.14	.40	.09	.29	.23	.08	.14	.17	1.00

S = number of segments in a model; ρ_s = mixing proportion of latent segment (s); AIC = Akaike's information criterion; BIC = Bayesian information criterion; CAIS = consistent AIC; EM = normed entropy criterion.

Table 1. Information and Classification Criteria for Varying S and Segment Sizes

In the next analytical step, the FIMIX-PLS module was applied to the data, as explained earlier. To start with, FIMIX-PLS results were calculated for a two-segment model. The number of segments was then successively increased. We stopped at a seven-segment model, because the results became unacceptable thereafter (e.g., path coefficients > 1), due to the existence of many segments with very small sizes (Trincherá et al., 2008). A comparison of the segment-specific information and classification criteria, as presented in Table 1, shows that a solution of three EP user segments is the most appropriate. All relevant information criteria (AIC, BIC, and CAIS) are higher for all other segment solutions. The choice of three segments is also supported by the EN value of 0.59. For all

other solutions, the EN value is lower, reflecting an increase in segment fuzziness. Next, the observations are aligned to each segment based on their segment membership's maximum probability. Regarding segment sizes (see Table 1), we see that after the three-segment solution, as the number of segments increases, the smaller-sized segments are gradually split up to create additional segments, while the larger-sized segments remain relatively stable. The analysis allows us to conclude that, in the data set, there is a relatively large segment ($\rho_2=0.53$), a medium, stable segment ($\rho_3=0.37$), and a small, fuzzy segment ($\rho_1=0.10$) of EP users.

Figure 1 and Table 2 present PLS path model results for the global model and the three latent segments. The data sets of the three segments were used separately as input matrices for the manifest variables to estimate the PLS path model for each group of individuals. Prior to evaluating goodness-of-fit measures and path coefficients, all outcomes regarding the segment-specific models were tested regarding reliability and validity (as discussed earlier). The analysis revealed that all measures satisfy the relevant criteria (Henseler et al., 2009). All path estimates except one are found to be significant, at the 0.001 level. When we compare the global model with the FIMIX-PLS results of the segment-specific models, we find that the latent variables' importance and effect vary substantially between the various models. For example, while collaborative support is the most important driver of EP utilitarianism in the global model ($\beta=0.41$), for individuals in Segment 3 it is ergonomicity ($\beta=0.34$). Furthermore, the effects' strengths also vary substantially. While the strength of the path collaborative usefulness \rightarrow utilitarian value is only medium in the global model, it is very high ($\beta=0.96$) for EP users in Segment 1. Likewise, all EP user segments differ considerably with regard to the six relationships between the constructs.

	FIMIX-PLS			
	Global	s = 1	s = 2	s = 3
Facilitating conditions \rightarrow Ergonomicity	0.51*	0.90*	0.25*	0.77*
Facilitating conditions \rightarrow Collaborative support	0.26*	0.33*	0.19*	0.22*
Facilitating conditions \rightarrow Utilitarian value	0.12*	0.00*	0.04 ^{ns}	0.24*
Ergonomicity \rightarrow Collaborative support	0.53*	0.65*	0.40*	0.70*
Ergonomicity \rightarrow Utilitarian value	0.24*	0.09*	0.18*	0.34*
Collaborative usefulness \rightarrow Utilitarian value	0.41*	0.96*	0.34*	0.30*
ρ_s	1.00	0.10	0.53	0.37
n	5,783	578	3,065	2,140
$R^2_{\text{Ergonomicity}}$	0.26	0.57	0.88	0.38
$R^2_{\text{Collaborative support}}$	0.49	0.30	0.70	0.23
$R^2_{\text{Utilitarian value}}$	0.46	0.00	0.75	0.31

n = number of observations in data set, * significant at 0.001, ns= not significant

Table 2. Global Model and FIMIX-PLS Results of Three Latent Segments

5 Conclusion

To develop a complete understanding of information systems users, researchers must incorporate segment-level differences or heterogeneity in their analysis. Our particular interest is to better understand heterogeneity in SEM (which cannot be achieved by other techniques, such as simple clustering), and specifically models that link system ergonomicity and system functions with user productivity. For example, is user productivity primarily driven by reducing cognitive load when interacting with information systems for some, and providing functionality for others? From our preliminary analysis, it is clear that aggregate (global) productivity model results can be misleading. Aggregate analysis hides the existence of meaningful subsets of system users that are more homogenous in the productivity drivers. The model allows managers as well as researchers to conduct a response-based segmentation and at the same time explicitly allowing for both measurement and structural error.

While some users are primarily concerned with ergonomicity, others users' productivity is the result of functionality. The segment sizes help identify the important user groups. Segment 2, the "heavy user" group (3,065 people) is more important and a major focus of research and management than Segment 1, the "light user" group (578 people). Given that resources are limited, one would first seek to improve heavy users' specific productivity drives. Our use of finite mixture-based segments built on PLS can help organizations draw more reasonable conclusions that those based on descriptive variables alone, such as frequency of system usage. The next part of our research, discussed in the following section, focuses on finding exploratory variables (e.g., age, gender, experience, task/ job characteristics, etc.), that characterize the three user groups and therefore further improve interpretability.

6 Future Research

The research presented in this paper considers the Steps 1 and 2 of Ringle et al.'s (2010a) FIMIX-PLS approach. To complete our analysis, our future research activities will also incorporate the proposed Steps 3 and 4, which uncover explanatory variables through ex post analysis. The results of this analysis will finally allow for an interpretation of the segmentation that we have achieved so far. It will allow researchers as well as practitioners to identify unobserved moderating factors which account for heterogeneity which in turn will enable them to link segment membership to observable individual-level characteristics (e.g., socioeconomic and demographic variables) and improve the productivity gains from employee portals. As an indication of how we proceed with this research endeavor, we outline the next steps as an outlook.

In the FIMIX-PLS Step 3, an explanatory variable must be uncovered in ex post analysis. This explanatory variable, which serves as input for segment-specific computations, is used to classify the data. The variable must include both the similar grouping of data, as indicated by the FIMIX-PLS results, as well as the interpretability of the distinctive clusters (Ringle et al., 2010a). Approaches for systematically uncover explanatory variables that fit the FIMIX-PLS results are available. A statistical procedure to conduct ex post analysis of the estimated FIMIX-PLS probabilities has been proposed by Ramaswamy et al. (1993). Likewise, logistic regressions, CHAID analyses, and classification and regression trees can be applied to identify variables that can be used to classify additional observations in one of the designed segments.

In contrast to these systematic searches, a logical search can focus on the interpretation of results. In such an approach, variables with high relevance for explaining the expected segment differences are analyzed with respect to their ability to form observation groups that match the FIMIX-PLS results. Accordingly, in FIMIX-PLS Step 4, multi-group PLS path modeling (Dibbern and Chin, 2005; Henseler, 2007) analyses will be conducted. In the case of significantly different group-specific path model estimations, further differentiated interpretations of PLS modeling results are possible (Ringle et al., 2010a).

Having finished this research project, the results will contribute to both research and practice. By identifying the user-specific success factors of employee portal utilitarianism, our findings will advance theoretical development in the area of collaboration-centered systems. Furthermore, the study's study will enable practitioners to better understand the levers with which to improve their employee portals subject to specific user segments.

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