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EXPLORATIVE CLUSTERING OF CLINICAL USER PROFILES: A FIRST STEP TOWARDS USER-CENTERED HEALTH INFORMATION SYSTEMS

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Abstract

The literature in health information systems and medical informatics reports contradictory findings with regard to acceptance, routinization behavior, and use of technology in healthcare. A possible reason for that is the deficiency of certain studies to adequately conceptualize health professionals as «users» of technology. From a pragmatic view, many clinical systems suffer from a lack of user-centricity, which often provokes a certain level of resistance or negative attitude toward technology among health professionals. Clinical user profiles may be a first step in assisting researchers and practitioners in designing more user-centered systems as well as more precise usability and adoption studies. By means of an exploratory cluster analysis based on the answers of an online survey with 108 health professionals, three different user profiles were identified: the «delegator», the «all-rounder», and the «supporter». It is expected that the presented alternative view on users of health information systems may allow scientists to improve the explanatory power of value assessments and usability studies as well as designers to better adapt their solutions to the context and interests of health professionals.

Keywords: E-Health, Design for Use, Health Information Systems, Technology Acceptance, User Profiles.

1   Introduction

The adoption of information systems (IS) and information technology (IT) in healthcare is perceived as one potential solution to tackle many of the current and upcoming problems in western societies such as continuously increasing public spending, the ageing of populations, and the subsequent higher demands related to effectiveness, efficiency, and quality of health services (cp. Goldschmidt, 2005; Khoumbati et al., 2006; LeRouge et al., 2007). Still the healthcare industry shows a relatively slow IS/IT adoption rate (Avison and Young, 2007; Poon et al., 2006), although a significant relation between the financial wellbeing, size, and productivity of a healthcare organization and its level of IS/IT adoption is reported in many studies (Fonkych and Taylor, 2005).

Albeit the question remains unanswered whether healthcare organizations with greater profits from operations and total assets can afford more sophisticated investments in IS/IT (and are therefore more productive than others), or IS/IT itself has a positive effect on the organization's performance, it is a well known circumstance that resistance to IS/IT is considerably high in almost any healthcare organization. In the course of trying to understand and explain this reserved attitude of health professionals towards IS/IT, many group or individual-level studies fail to conceptualize the role of the «user» correctly, introducing a severe distortion to the reported findings by potentially examining the wrong perceptions on IS/IT usage. As a result many studies comprise a population bias: "All stakeholders are not users. A physician who reads a report generated by a clinician that operated some technology is not the «user» of the technology" (McLeod Jr. and Guynes Clark, 2009). We are aware that this kind of bias is but one source of error in healthcare IS/IT adoption and usability studies (Adelman, 1991). Other potential bias emerges when statements about the qualities of a technology are collected from a single source or homogenous group, which shares a common educational background, personal position or knowledge deficiency (key informant bias); when the independent and/or dependent variable(s) are defined incorrectly causing a multiple-treatment interference, interaction of history and treatment effects and so forth (ecological bias); or when an extraneous variable correlates with both the independent and the dependent variable (cofounding bias).

While the latter error types are in most instances extremely study-specific (and thus are difficult to be solved by generalized rules or guidelines), we think that it is of great value to identify meaningful categories for classifying distinct health information systems (HIS) users (or «user profiles») in order to characterize a study's population more precisely and draw more differentiated conclusions from the findings of adoption and usability studies. The identified user profiles also have a practical value: A deeper knowledge about different roles and habits of users may help to design more user-centered appliances and improve human-machine-interaction (Fernandes, 2012). We think that the usual distinction between clinicians (or physicians) and nurses is too superficial for explaining IS/IT adoption behavior (and resistance) in clinical practice and hope that our attempt in exploring different user profiles is useful to practitioners and researchers in this specific area, especially for the design of new systems and the conduct of evaluation studies. In this sense, with this paper we strive to address the following research question:

> *What are purposeful user profiles for health professionals working in a clinical environment?*

The remainder of the paper is structured as follows: In the next section we describe the theoretical grounding of this work. Based on the reviewed literature, we then explain our approach and sample for identifying distinct user profiles of health professionals in clinical environments. In the section that follows, the results of the conducted cluster analysis are interpreted and discussed in more detail. Lastly, we highlight the major practical implications as well as make some suggestions for the continued research in this field.

2   Theoretical Grounding

In the extant literature, a user profile generally is understood as an "accurate representation of a user's interests" (Trajkova and Gauch, 2004). To build such a profile, two strategies are conceivable: (i) implicit formulation, for example by observing the behavior of users, or (ii) explicit formulation by

directly asking users questions about their usage behavior. In both cases it is a recommended approach to delineate possibly relevant factors that may affect usage behavior prior to starting the investigation.

In identifying possible observable measures for determining distinct user profiles, a review of the general as well as healthcare-specific IS literature on user acceptance, routinization behavior, and use of technology was conducted. The analysis revealed seven major factors that may directly or indirectly influence usage behavior and thus be useful for specifying user profiles (Table 1).

Factors	Explanation / Definition	Literature	Relevance to HIS user profiles	Possible observable measures
Demographic influence	Degree to which a user's behavior is influenced by characteristics such as age or gender.	(Dwivedi and Williams, 2008)	There is strong evidence that demographic variables directly affect usage behavior.	1) Age 2) Gender
Social influence	Degree to which a user's behavior is affected by the beliefs of important others.	(Jeyaraj and Sabherwal, 2008); (Succi and Walter, 1999)	The role of interpersonal agreements, culture, and subjective norms imposed by peers is particularly high in closed professions such as medicine.	3) Experience/ career level
Trust	Degree to which a user's behavior is influenced by his/her perception that a technology is capable of facilitating a task.	(O'Connor et al., 2012)	As compared to other constructs, there is little evidence that shows that trust directly influences usage behavior.	4) Trust level
Habits	Degree to which a user's behavior is influenced by learned sequences of acts that have become automatic responses to specific cues.	(Limayem and Cheung, 2008; Mettler 2012; Verplanken and Aarts, 1999)	There is empirical evidence that habits greatly dominate a user's interaction pattern as well as affect continuance behavior.	5) Usage time / regularity of usage 6) Habitual tasks/ cure vs. care
Performance expectancy	Degree to which a user's behavior is influenced by his/her perception of the outcome of technology usage.	(Holden and Karsh, 2010); (Hennington and Janz, 2007)	There is strong support that the intention to use a technology is affected by expected benefits a technology potentially delivers.	7) Job performance
Effort expectancy	Degree to which a user's behavior is influenced by his/her perception that operating a technology is relatively difficult to learn.	(Paré et al., 2006)	The complexity respectively comprehensibility of a technology critically affects a user's continuance behavior.	8) Task-technology fit / integration into clinical work routines
Facilitating conditions	Degree to which a user's behavior is affected by internal and external constraints such as self-efficacy, computer literacy, or availability and compatibility of resources.	(Shaw and Manwani, 2011)	Empirical evidence exists which confirms that advanced training and an adequate infrastructure positively influences usage intention and behavior.	9) Computer literacy level

Table 1.   Possible influencing factors affecting cognitive beliefs and behavior of HIS users.

3   Methods

In order to discover possibly meaningful user profiles of health professionals in clinical environments, we used an exploratory cluster analysis as the underlying research method. According to Hair et al. (2006) cluster analysis is an inductive and purely empirical, statistical technique for classification or

the partitioning of data into meaningful subgroups. It is particularly useful, when the number of subgroups and other information about their composition is unknown (Fraley and Raftery, 1998). Unlike other statistical classification techniques, such as discriminant analysis, only rudimentary assumptions have to be satisfied for its application, such as representativeness of the sample and unidimensionality of the underlying variables (Punj and Stewart, 1983). Because of its seemingly boundless aptitude to identify groupings in any dataset, it has widely been applied in IS research, such as for studying the processes by which individuals adopt IS/IT innovations (Jeyaraj and Sabherwal, 2008), for determining distinct categories of IT artifacts (Yeung and Lu, 2004) or general IS/IT user types (Bucher and Dinter, 2008).

3.1   Application of Multivariate Grouping through Cluster Analysis

Besides the mentioned favorable application in IS research and practice, cluster analysis has not been untroubled by criticism. For instance, Punj and Stewart (1983) argued that, unlike factor analysis or regression analysis which tended to be the special province of a particular discipline, there is no dominant discipline expediting the development of new clustering algorithms and providing guidance in the use of these methods. Consequently, no clear application guidelines exist, making cluster analysis a somehow 'fuzzy' approach.

In view of this criticism, Balijepally, Mangalaraj and Iyengar (2011) studied the IS researches' usage practices of cluster analysis and derived the following guidelines for its application in IS/IT, which we adhered to in the course of our analysis:

(1) Clustering variables: The variables selected for describing the objects being grouped should emanate from past research or explicit theory and be consistent with the study's objectives. The approach for variable selection should be explicit and be categorized as being inductive, deductive, or cognitive (Ketchen and Shook, 1996). It's unclear whether to use or not to use standardized variables; a conservative approach is to conduct the analysis with and without standardized variables and adopt the solution with the higher validity. Application to this study: As discussed in the previous section, the clustering variables used in this study were derived from existing theoretical work.

(2) Clustering algorithm and similarity measures: Clustering methods range from largely hierarchical procedures (Ward, 1963) to more relocation-based, iterative partitioning strategies (MacQueen, 1965). A definition of clear guidelines when to use which algorithm was not specified by Balijepally et al. (2011). However, in order to counter the limitations of the hierarchical and non-hierarchical clustering algorithms, they advise to use both in tandem and compare the results as well as to use different measures for estimating the resemblance between the entities being clustered. As different distance measures may produce different cluster solutions, it is recommended to use several distance measures and compare the calculated clusters with theoretical or known patterns (Hair et al., 2006). Application to this study: Different clustering methods available in SPSS 18.0 were tested, which yielded throughout stable results. As a matter of convenience, we only present the results obtained from a hierarchical clustering basing on the Ward's method using a Squared Euclidean distance measure.

(3) Number of clusters: Different measures, such as the agglomeration coefficient or the cubic clustering criterion, for specifying the number of clusters exist. It is recommended to apply practical judgment, common sense, or theoretical foundations when defining the final cluster solution. Application to this study: The number of clusters was derived using both, statistical coefficients and a graphical plot, referred to as dendogram (Figure 1).

(3) Validation of clusters: The reliability of the cluster solution should be verified by assessing the stability of clusters using multiple algorithms (Ketchen and Shook, 1996) or splitting the sample (Punj and Stewart, 1983). External validity is tested by clustering on a hold-out sample using the same variables and assessing the similarity of the two solutions; however, this is only applicable in generalizable or unspecific settings. Significance tests should be applied for assessing the criterion-related validity. Application to this study: Reliability was tested by means of a split-half test. Criterion-related validity was assessed performing a one-way analysis of variance (Table 3). Since a cluster analysis always finds clusters, the content-related validity cannot be tested per se. The interpretation of the meaning of the resulting clusters is an act of theorizing.

3.2   Data Collection and Sample

The data for the cluster analysis is part of a longitudinal investigation and was obtained from an inquiry, which aimed at measuring cognitive beliefs and affects of health professionals that were actively involved in the evaluation of a new electronic medical records system (EMR) in a larger private hospital. As a first step, to determine the basic population for this survey, we inspected the old and new EMR system's log files. This resulted in a list of a total of 746 registered users, respectively potential respondents. In a second step, in order to assure that the health professionals have basic knowledge about the EMR system, the initial total population was restricted to individuals who previously have attended the EMR introductory training course. This resulted in a list of 200 health professionals with sufficient knowledge about the practical use of the EMR. These 200 individuals were invited to participate in an evaluation survey and were asked to complete an online questionnaire concerning their EMR usage behavior. The form consisted of several blocks of questions, including questions related to their personal profile, working habits, attitude towards using the EMR in future and other general questions regarding effort and performance expectancy using a 5-point Likert scale. Participation was voluntary and confidentiality was guaranteed. The draft version of the questionnaire was checked beforehand by leading nursing and medical staff, with a view to removing any inconsistencies and generally improving the structure and understandability of questions. We received 108 valid responses (or 54% response rate) from all major medical disciplines of the hospital under study. The sample includes answers from amongst others: anesthesiologists, cardiologists, critical care and emergency nurses, doctors of general medicine, gynecologists, orthopedics, urologists, and visceral surgeons.

4   Results

In this section we describe the results of the conducted cluster analysis and provide an interpretation of the numerical solutions. A detailed discussion of potential implications for theory and practice will be provided in the next section.

4.1   Identification of Clusters

The initial analysis of multiple clustering criteria suggested the existence of two or three distinct clusters across the nine identified clustering variables (Table 1), which were used to study different user interaction patterns and routinization behaviors of the hospital's health professionals. From the agglomeration schedule in Table 2 a major change in the coefficients between step 2 and 3 (and a lesser but still significant shift between step 3 and 4) can be observed, exhibiting an optimal number of two different categories of clinical systems' users.

No.of clusters	Agglomeration step	Co-efficient this step	Change
2	12647.56	4307.06	8340.50
3	4307.06	2505.24	1801.82
4	2505.24	1858.15	647.09
5	1858.15	1486.06	372.09
6	1486.06	1204.02	282.04

Table 2.   Agglomeration Schedule.

From the interpretation of the graphical results of the cluster analysis (Figure 1), the differentiation between three distinct user types of clinical systems may also be a reasonable solution. As there is no test for clearly determining the exact number of clusters, we opted for selecting the three-cluster model in order to obtain a broader range of distinct user profiles to be discussed.
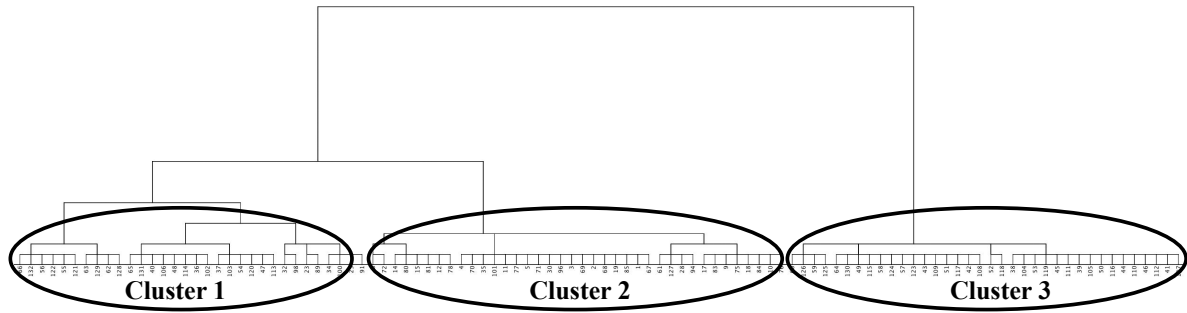
Figure 1. *Graphical representation of the hierarchical clustering (dendogram).*

Table 3 outlines the results of a one-way ANOVA test for differences in the variables affecting the cognitive beliefs of the surveyed medical professionals. The results indicate that not all differences between the three clusters were significant. Still a great proportion of the overall variance in each cluster was explained.

Variables	Cluster			Mean (SD)	F Value	Sig.
	1	2	3			
1) Age	4.34	4.15	2.67	3.66 (1.01)	26.01	0.00
2) Gender	1.92	1.48	1.17	1.56 (0.50)	19.31	0.00
3) Experience / career level	3.17	3.08	2.98	3.09 (0.70)	0.37	0.69
4) Trust level	3.00	3.61	3.56	3.36 (1.15)	2.11	0.10
5) Usage time / regularity of usage	2.43	2.22	1.80	2.19 (0.52)	0.72	0.48
6) Habitual tasks/ cure vs. care	1.20	1.17	4.00	2.17 (0.72)	28.41	0.00
7) Job performance	2.24	2.00	2.17	2.14 (0.69)	9.50	0.00
8) Integration into clinical work routines	4.62	4.49	4.97	4.67 (1.12)	0.96	0.38
9) Computer literacy	1.00	1.43	1.83	1.38 (0.49)	28.51	0.00

Table 3. *Cluster analysis across user group of distinct medical disciplines.*
Cluster 1 (n= 38); Cluster 2 (n=37); Cluster 3 (n= 33).

In order to allow a rather comprehensible comparison of the extent to which the three emergent user profiles differ from each other, a visual representation is provided in Figure 2.

The first user type (rectangles) exhibits strong characteristics of seniority, being rather at the end of a professional career as specialist in cure activities (i.e. treating solely diagnosable medical conditions), but without solely focusing on it. Although the own computer literacy is appraised as being deficient for today's work environment, still positive reactions with regard to an EMR general usefulness and applicability is expressed. However, trust in and the effective use of clinical systems is low. The majority of users belonging to this group were males.

The second group of users (triangles) consists of users in mid career, also having a long educational track record, but differing from the first profile in that the gender of this group of professionals is more heterogeneous and the estimated computer literacy is higher. Moreover, the use of the EMR is exclusively focused on activities related to the cure of patients. Generally, the use-related beliefs of this group are worse compared to the first user type, but still attributing a rather positive impact of EMR on their job performance. Although this group uses the EMR more frequently than the first user

type, its integration into daily work routines is seen to be more difficult. However, there is more trust in technological advancements, as opposed to the first user type.

Finally, from Figure 2 it seems apparent that the first two user types strongly differ from the third profile (circles). Major differences can be found in the manner how an EMR is estimated to impact the job performance, the main area of application (i.e. care activities), the educational background, gender, and the level of professional experience. A major difference can also be found in the frequency of usage. Compared to the first two groups it seems that this user type interacts more frequently with the EMR, possibly also leading to an increased trust in the used technology. Yet this user type is much less satisfied.
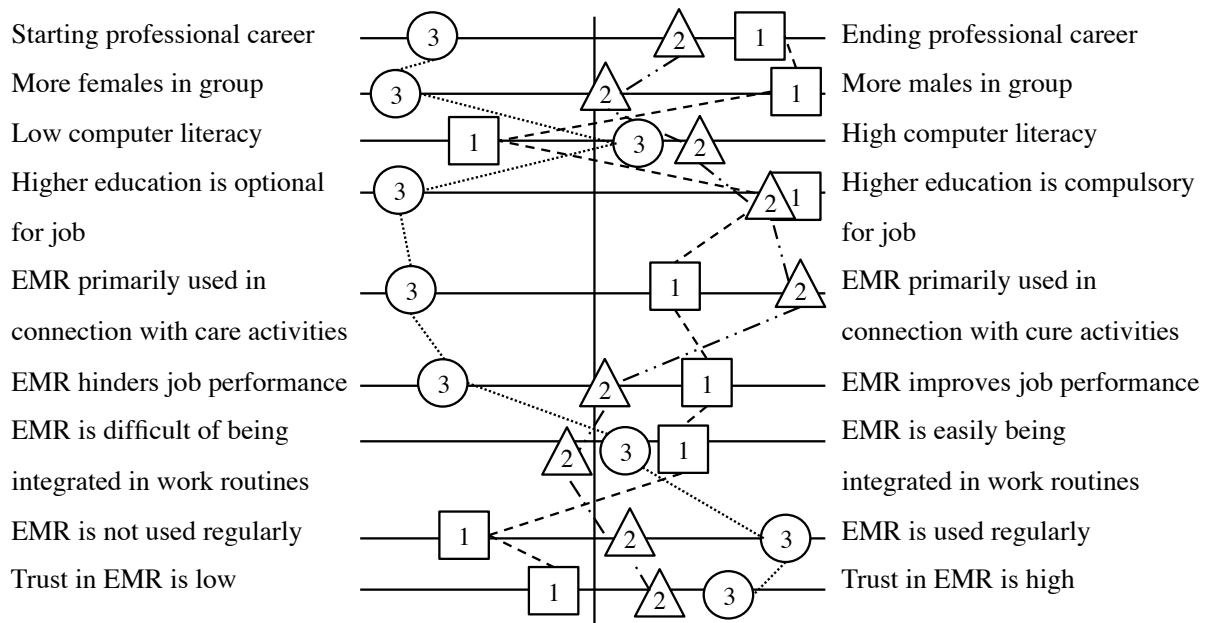

Figure 2.   Distinct profiles of user types in clinical environments.

4.2   Interpretation of Clusters

As mentioned earlier, it is not possible to definitively ascertain the validity of the results of a cluster analysis, since there is always the need for an interpretation of the numerical solutions. Contrariwise, a limitation to a pure quantitative analysis may not lead to a practical outcome, i.e. an incisive definition of distinct user profiles in clinical environments. In this sense, and acknowledging the subjectivity of our complementary qualitative interpretation of the results, we characterize three distinct profiles of clinical systems users.

Interpretation for cluster 1:

The delegator user profile*:* The «delegator» is not necessarily centered on a particular specialization of activities. Either cure or care is relevant in daily work routines. He/she earned the label because of the low level of computer literacy and usage time with the clinical system, possibly indicating that information is gladly consumed, but not when it means a personal interaction with the system. Being rather a senior person, the needed information may be gathered and maintained by others. Although trust in technology is not high, its value for the potential treatment of patients is well understood. Typical examples for this user type are, for instance, general practitioners conducting frequent medical interventions in hospitals or (head) nurses with additional medical educations.

Interpretation for cluster 2:

> **The all-rounder user profile**: The second group of users in clinical environments is consists of professionals that use technology on a more regular basis for specific tasks related to the cure of medical conditions. The interaction with the system is not gushily appreciated, but its necessity is comprehended and its use more or less well integrated in the daily work routines. Being an «all-rounder» in the middle of the career, the professional handling with information technology is estimated to be an important part of the job. Examples for this user type are aspiring clinical specialists or experienced nursing staff.

Interpretation for cluster 3:

> **The supporter user profile**: The last group of users is composed of rather young medical professionals with a high affinity to and trusts in technology. Being at the start of their career, the focus of daily work routines is rather on the care of patients. Having the role as «supporter» means that information frequently is gathered and maintained for others, often impacting the performance of his/her own job. However, in order to accomplishing the quotidian duties efficiently, the interaction with the system is well integrated in the daily work routines. Assistant physicians or untrained nurses are examples for this category of users.

5 Discussion and Conclusion

The lack of understanding the nuances of the «user» as central concept in HIS adoption and usability studies often leads to equivocal results with respect to the acceptance, routinization behavior, and use of technology. A differentiated application of research models such as TAM, UTAUT and others for studying user acceptance and routinization behavior is, however, crucial to come to meaningful and truthful results. As stated by McLeod Jr. and Guynes Clark (2009), knowing the user is one of the most important principles for doing research in HIS. The typical differentiation between clinicians, physicians, and nurses might, in some cases, be adequate; but for a more in-depth analysis of the root causes of different user behavior and user acceptance as well as for designing user-centered information systems, a more 'shading' approach for classifying users in clinical environments is needed.

5.1 Implications for Theory and Practice

The presented alternative view on the HIS users may allow researchers to improve the explanatory power of value assessments and usability studies, thereby hopefully diminishing or at least relativizing some of the contradictory findings. It is of utmost importance to make a clear characterization of the sample (the users of the technology under study). Specialization in healthcare is quite high, leading to very homogeneous teams with more or less the same educational background, and sometimes even similar «world views» (Glouberman and Mintzberg, 2001). Seeing these teams as user groups (respectively deducing user profiles based on group membership) is an erroneous belief and may lead to wrong conclusions. As the findings of this paper showed, perceptions and usage behavior of health professionals are not necessarily dependent on medical disciplines but rather on factors such as personal experience, social status, age, gender, computer literacy, or trust.

From a pragmatic perspective, the results of this study are equally of value to both scientists and professionals interested in practical problem-solving: Within a typical (user-centered) design process (c.p. International Organization for Standardization, 2010; Offermann et al., 2009; Peffers et al., 2007), the identified user profiles may assist design science researchers and professionals in better understanding the context of the design problem as well as in enhancing user-centricity by adapting the generic design solutions according the identified peculiarities of each profile (Figure 3). This is particularly helpful when the designer is not familiar with the healthcare domain or needs some empirical findings for improving the personalization of the system. Lastly, the user profiles may also guide hypothesis generation and theorizing to a certain extent (e.g. constraints of personalized medicine).
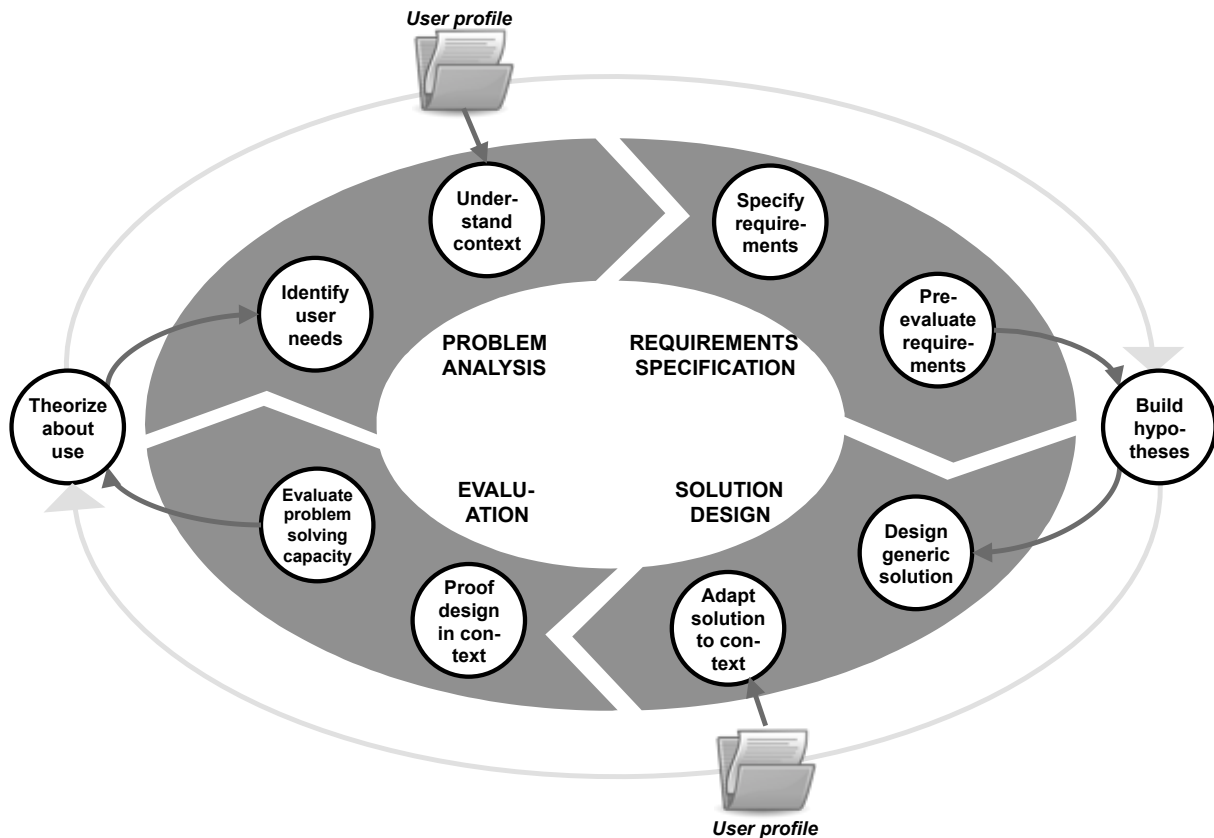
Figure 3.   *The role of user profiles in user-centered design and research.*

5.2   Limitations and Outlook

In this paper we present a categorization of user profiles that goes beyond the usual differentiation of doctors and nurses, distinguishing users in clinical settings based on the influencing factors that potentially affect their cognitive beliefs and perceptions on the usage of technology. The exploratory cluster analysis yielded some further interesting results that are worth exploring in more detail. On the one hand, it seems necessary to particularize as well as back up the interpretation of the clusters by means of additional field reports or expert interviews. In doing so, also the comprehensibility and practicability might be tested. On the other hand, it is essential to expand the data collection in order to put the empirical analysis on a firmer footing. A broader data basis might facilitate further comparisons between different organizational scenarios (e.g. city hospital vs. rural hospital) or country-related peculiarities as this study is based on the experiences of a one larger private hospital in one particular country.

In addition, we limited our scope to users of clinical systems only (cp. framework as discussed in Mettler and Raptis, 2012). We therefore excluded systems in the peripherals outside a healthcare organization (e.g. at home of the patient) or systems with a particular focus on non-medical professionals or patients. In view of the broader adoption of patient-centered systems (Krist and Woolf, 2011) also new user profiles for health professionals may emerge.

Besides a differentiated view on the user in healthcare, future studies may also provide more evidence how to better categorize different IS/IT applications. The understanding of what comprises a clinical system, such as a definition of the basic features of an EMR, more often than not considerably differs in HIS adoption studies. Hence, not only a more critical examination of the user concept but also a more discerning debate on the HIS boundaries is required to really being able to disclose the current state and potential success factors of IS/IT adoption in healthcare.

Finally, there is still a considerable proportion of medical professionals avoiding or not using IS/IT at all (Kane and Labianca 2011). More research is needed to fully understand their dread or animosity

towards technology usage. Given the case that this group will persist in future, the suggested classification of user profiles might be expanded by an additional «avoider» profile.

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