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Methodological Implications of Research on Technology Use by Healthcare Professionals: A short Introduction to Multidimensional Scaling

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Abstract. Healthcare professionals currently face different challenges in an ongoing reconstruction of care. Digitization and the use of healthcare-related technologies promise both an improvement in quality of care and an increase of treatment efficacy. Especially telemedicine systems seem to be capable to overcome current spatial and temporal limitations of care. As telemedicine appears to be a non-uniform term describing a variety of technological characteristics, the explanatory power of entrenched models for technology use varies across different contexts of use. To explore important contextual factors in the field of healthcare technology research and to enrich the methodological diversity in Information Systems research, this paper provides a short introduction to Multidimensional Scaling. Being able to visualize underlying dimensions of subjective perceptions, Multidimensional Scaling shows complementary applicability and use with regard to elaborated methods and a high integrability into holistic research strategies.

Keywords: Information and Communication Technologies (ICT), Telemedicine, Multidimensional Scaling, Phenomenology, Healthcare

1 Introduction

Information and Communication Technologies (ICT) are recently discussed in their function of highly potent accelerators and catalysts for digitization processes in healthcare (Krick et al., 2019). In its basic function to enable and extend interaction between persons and organizations, ICT promises to address different challenges present in many healthcare systems all over the world. While demographic change and the increase of multi-morbidity among elderly patients (Svensson, 2019) result in a need for coordination of interdisciplinary and intersectoral care, simultaneously an agglomeration of healthcare professionals in urban areas complicates an equitable delivery of care (Wilson et al., 2009). Meanwhile, Primary Care Physicians (PCP) serve as important coordinators in healthcare systems, as they regulate access to general and specialized (medical) care (Bashshur et al., 2016). Therefore, PCPs and their use behavior concerning healthcare-related technologies are of special interest. In the ongoing debate about ICT and its potential to improve quality of care, the use of telemedicine systems in primary care becomes a prominent issue, as telemedicine systems might be able to overcome spatial and temporal limitations (Bashshur et al., 2016). From this objective, the necessity arises to define theoretical and methodological foundations of research. Primary care consists of many dissimilar facets due to a high variety of medical cases and treatments, while the concept of telemedicine comprises different technological settings (e.g. messaging, medical advice via telephone, audiovisual appointments, etc.). Therefore, generalizing, deductive research methods focusing on user acceptance show some limitations that might be encountered by increasing the methodical variety of research. In this context, a method is needed that is able to explore subjective latent dimensions of technology use, but simultaneously provides the possibility to deduce intersubjective results integrable into structural models. This paper addresses this issue by proposing Multidimensional Scaling as a complementary method and provides legitimation of theoretical considerations.

2 Theoretical Background

Telemedicine appears to be feasible to address current issues concerning different challenges of healthcare systems, as it "provides a virtual environment that enables remote interaction between healthcare professionals and their patients, and among healthcare professionals themselves" (Flumignan et al., 2019, p. 184). From this broad definition, different aspects concerning the concept of telemedicine arise: (1) There are different kinds of technology associated with telemedicine. "Virtual environment" might refer to telephone consultation (Baumeister et al., 2014), a combination of telephone advice and text messaging (van den Berg et al., 2015), an audiovisual appointment between physician and patient (McConnochie, 2019), or other forms of virtual interaction. (2) Telemedicine can be applied to different persons and different numbers of persons. Aside from a direct connection between physician and patient (Reed et al., 2019), other healthcare professionals might as well use telemedicine to connect with patients or other healthcare professionals (Marcolino et al., 2013). (3) Different patients or groups of patients can be addressed through the use of telemedicine systems. While some studies focus on heterogeneous groups of patients in primary care, e.g., patients with non-specific chronic diseases associated with a single PCP's practice (Orozco-Beltran et al., 2017), others report the use of telemedicine for very specific diagnostic procedures, but for a whole population of patients (Stanimirovic et al., 2020). These aspects show that studies investigating factors constituting user acceptance of telemedicine systems are not easy to compare. The explanatory power of generalizing models to explain user acceptance, e.g., the Technology Acceptance Model (TAM) (Davis, 1989), therefore varies strongly across different contexts of telemedicine use by healthcare professionals (R^2 varies from 0.161 to 0.78 in a review of different theoretical models predicting end user acceptance by Harst et al. (2019)). Thereby, uncertainty about an actual positive effect on patient related outcomes might even intensify the prediction of user acceptance amongst healthcare professionals. Designated the highest standard for systematic reviews in evidence-based healthcare, the Cochrane Library lists twelve different reviews directly addressing issues of telemedicine and its general usefulness in different medical disciplines. In summary, the majority of these reviews leads to the impression that sufficient evidence for an actual positive effect on patient outcomes is currently not given (Flumignan et al., 2019).

Taking into account these current issues in research on telemedicine systems and user acceptance of healthcare professionals as well as considering the importance of theoretical contextualization to improve description, explanation, and prediction of relevant phenomena (Hong et al., 2014), one might ask for a theoretical approach to formulate methodological implications that are able to enrich the current set of methods used for research. Phenomenology appears to be an evolving approach in healthcare research to explore context-specific facets of phenomena (Carel, 2011), while being considered relevant for explaining healthcare professionals' use of digital technologies (Müller et al., 2020). Generally speaking, a phenomenological approach focuses on subjective human experience, e.g., using a telemedicine system to advice patients in a critical situation related to their chronical disease. To understand a phenomenon completely, such an approach asks to explore contextual (subjective) facets of the phenomenon and, by comparing it with similar experiences, extract the essence of it (Husserl, 2019). Such essential factors might then be integrated into generalizing (existent) models to be tested deductively. Introna and Ilharco (2004) demonstrate such a phenomenological *reduction* on the example of screens. While different research methods can be integrated into a phenomenological approach, in the context of user acceptance concerning telemedicine systems primarily explorative and inductive methods seem to be of interest. Following Carel (2011) on her assumption that human experience is based on perception, Multidimensional Scaling (MDS) offers an interesting statistical approach as it is capable to visualize individual perceptions on a specific objective and therefore makes it more accessible to analysis. Originating from psychology, an introduction of MDS in the context of technological use by healthcare professionals within Information Systems (IS) research is missing to date. The following section provides an overview of MDS and illustrates its value for this research field of IS exemplarily.

3 Methodological Implications

To understand contextual factors determining the use of telemedicine systems by therapists and patients, it is of great interest to explore their perception on relevance of a specific technology for their professional activity. Following a phenomenological perspective on human experience and its perceptual foundation, one possible way to explore the meaning of relevant technologies for therapists or patients is to analyze (dis)similarities of an individual's ideas about telemedicine (Introna & Ilharco, 2004). Therefore, one is able to recreate a therapist's or a patient's understanding of a 'useful' technology. One method that is capable of visualizing (dis)similarity data is called Multidimensional Scaling. In general, through using MDS one is able to arrange objects in a one- or multidimensional space with regard to their (dis)similarity. The configuration of objects, normally presented in two- or three-dimensional space, can then be interpreted through our visual senses, resulting in an intuitive way of analyzing even complex relations of objects (Borg & Groenen, 2010). In the following, a fundamental methodological introduction to MDS is presented. By comprehending the required statistical operations leading to an MDS configuration, the potential of this method to evaluate context specific aspects of technology use by healthcare professionals and patients unfolds.

An MDS configuration represents (dis)similarities of objects in an m-dimensional space ($m \in \mathbb{N}$). Therefore, it is the basis for an interpretation of underlying factors constituting (dis)similarities. The position of the included objects can be determined by different types of (dis)similarity data, i.e., correlations between objects or ordinal ratings of objects (i.a.). A typical method to collect data of ordinal ratings is to ask participants to compare sets of two different objects (e.g., technologies, countries, food), without specifying any underlying assumptions, on a Likert-scale (Borg & Groenen, 2010). In such a configuration, similar or highly correlated objects are close to each other, while dissimilar or weakly correlated objects are highly distanced (Borg et al., 2013; Borg & Groenen, 2010). To transform (dis)similarity data into distances within a visual representation, i.e., an MDS configuration, different types of distance functions can be used. The two most commonly used distance functions are the *Euclidean Distance Function* and the *City Block Metric*, which are both specific versions of the *Minkowksi distances*. The following formula is used to calculate the distance $d_{ij}(\mathbf{X})$ between an object i and an object j within an MDS configuration $\mathbf{X}$ by effectively summing up the differences of i and j in every dimension $a = 1, \dots, m$ and modelling values of $d_{ij}(\mathbf{X})$ through the parameter p:

$$d_{ij}(\mathbf{X}) = (\sum_{a=1}^{m} \left|x_{ia} - x_{ja}\right|^{p})^{\frac{1}{p}}$$

For p=1, the dimensional differences between two objects are summed up without actually modelling the resulting distance $d_{ij}(\mathbf{X})$. This kind of calculation corresponds the following visualization (Figure 1) of distance from one object A to another object B:

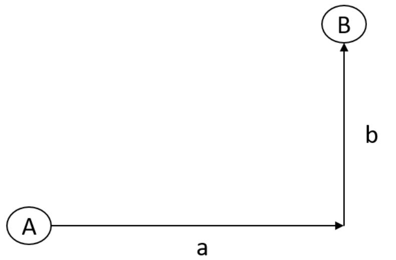

Figure 1. Calculation of distance within the City Block Metric.

The resulting distance is simply calculated through the addition of **a** and **b**. From its analogy to building structures of specific cities (e.g., New York) this kind of distance calculation is called *City Block Metric* (Borg & Groenen, 2010). In contrast, for calculating the Euclidean distance (p=2) between objects, dimensional distances are summed, squared, and finally their square root is taken. The following figure illustrates this kind of distance calculation:

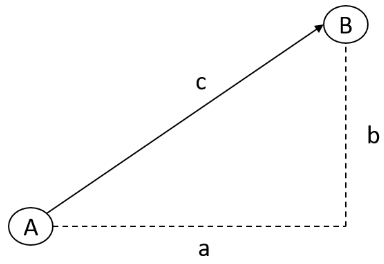

Figure 2. Calculation of distance within the Euclidean Distance Function.

The resulting distance between **A** and **B** in Figure 2 is **c**, calculated from **a** and **b**. MDS configurations are typically generated through an iterative process. Included objects are positioned in an m-dimensional space until their distances represent the objects' (dis)similarities as precisely as possible. For this step, different types of algorithms are used, e.g., *Torgerson scaling* or the *SMACOF procedure* (for more detailed information consider Borg et al. (2013, 81-86). To better interpret an MDS configuration, it is helpful to identify specific patterns of objects. Geometrical differentiations then need to be linked to content-related differentiations. In general, these content-related differentiations are based on heuristics, empirical and/or theoretical findings (Borg & Groenen, 2010). Figure 3 illustrates an example for an MDS configuration calculated with R (R Core Team, 2019) and the package *smacof* (Leeuw & Mair, 2009) using the *Euclidean Distance Function*. The configuration is based on data that results from pairwise ratings of healthcare-related technologies. Each data point represents an individual's comparison of two technologies on a 9-point Likert Scale (1-very similar to 9-very dissimilar). Overall, ten different technologies were rated (equal to 45 different ratings). For illustration in the context of this paper, data of the exemplary configuration was generated by the author's comparison of technologies that were discussed by PCPs and PCPs' assistants within a regional project about the digitization of home visits through tele-medical technologies. It is important to note that the assigned numbers on the dimensions of Figure 3 do not represent specific numerical values that can be assigned to the objects (especially the zero points of the axes), but are only for orientation. As a possible interpretation for the distribution of the objects in Figure 3, dimension 1 might represent the intensity of physical contact between healthcare professional and patient. Objects on the left (i.e., Blood Coagulation Monitor [BCM], Blood Glucose Meter [BGM], and Blood Pressure Monitor [BPM]) appear to be associated with the most invasive interactions involving the patient. For measuring the blood coagulation and the blood glucose level of a patient, it is necessary to extract capillary blood, while the measurement of blood pressure requires direct contact to a patient repeatedly, especially while palpating the patient's pulse. In contrast, objects on the right (i.e., Digital Medical Visit [DMV], Smartphone [SP] and Electronic Health Record [EHR]) are associated with an interaction of the healthcare professional with a specific technology, e.g., documenting relevant patient-related information in an EHR, without having actually physical contact to a patient. For dimension 2, the degree of digitization appears to be a possible explanation. As venoscopes and infrared thermometers for ambulant care are currently designed mainly for analogous use, technologies like a tele-medical stethoscope or a mobile Electrocardiogram [ECG] are capable to transmit data via remote connections between physician and patient or physician and physician's assistant. Furthermore, the already mentioned objects on the left, associated with more invasive interactions between physician (or assistant) and patient, are currently combined with automated data storage and/or transmission and therefore can be thought of as technologies integrating digital functionality. Noteworthy, the interpretation of specific geometrical distributions of objects in an MDS configuration depends on a priori assumptions, hypotheses, or heuristics of the person interpreting it. To visualize an intersubjective understanding of a phenomenon, different individual ratings can be summarized into a single configuration by using specific algorithms. As a result, a common geometrical space for different subjective ratings can be generated, from which generalizable tendencies can be deduced (Carroll & Chang, 1970).

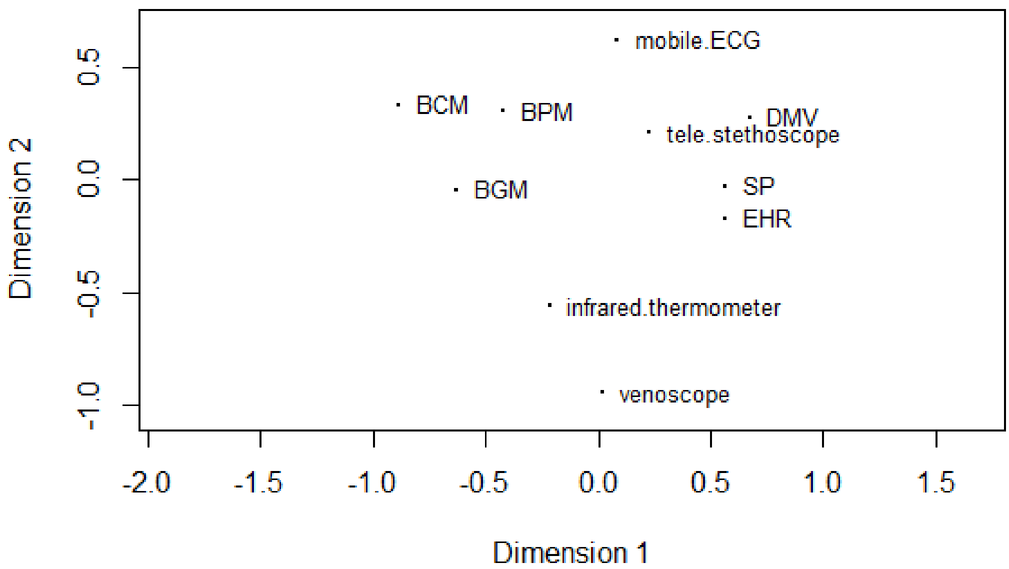

Figure 3. Exemplarily explorative MDS configuration for preference data

One possibility to visualize multiple individual perceptions on a set of objects (i.e., healthcare-related technologies in this context) is to use Unfolding Models, a type of Multidimensional Scaling that is based on hierarchical sorting. To evaluate the goodness of an MDS configuration, residuals are basically calculated through summing up the differences between configuration mapped distances and empirical (dis)similarity data. These residuals are then modified (e.g., through normalization) and transformed into different measures of fit, the so-called stress measures (Borg et al., 2013).

4 Discussion

In general, MDS can be used for both purposes to generate and to test hypotheses (Borg & Groenen, 2010). In its function to generate (or explore) hypotheses, MDS appears to be a suitable method to gain insights upon a research objective that needs to be further contextualized. Through the visualization of subjective and intersubjective perceptions regarding the (dis)similarity of specific objects, one is able to generate hypotheses, which can be tested deductively in the ongoing process of research. Although MDS is capable of illustrating subjective perceptions of a person or persons, qualitative interviews (especially semi-structured or open ones) normally generate more detailed insights. For a purely explorative approach, it might therefore be reasonable to conduct interviews before using preference data to select a group of analyzable objects for a later statistical analysis through MDS. Additionally, interviews conducted after explorative MDS might be very helpful to discuss the interpretation of an MDS configuration with participants, especially when it seems difficult to name dimensions of the configuration. While different qualitative interviews are not easy to compare because of their non-uniform structure, MDS configurations are calculated through a standardized process. By comparing different MDS configurations or integrating various individual configurations, intersubjective results can be generated.

Considering further inductive methods, explorative MDS and Exploratory Factor Analysis (EFA) both are utilized to find hidden structures in data. While explorative MDS is applied to find latent dimensions persons use for their judgements on specific objects or groups of objects (Borg & Groenen, 2010), the concept of EFA is based on the assumption that underlying factors account for relationships between specific variables (Kline, 1994). Although MDS configurations can be calculated through both subjective ratings and correlation of objects, EFA only uses the latter. As EFA is normally conducted with items based on psychometric assessments, one might argue that EFA requires a higher amount of a priori information than explorative MDS (for which subjective ratings are sufficient), but provides results that are easier to interpret. Analogically, confirmatory MDS and Confirmatory Factor Analysis (CFA) share a common requirement to formulate latent dimensions or factors to be tested, but differ in the extent to which such information has to be determined. As MDS and Factor Analysis therefore share a common understanding of latent dimensions constituting relationships between specific variables, MDS might also be utilized to inform structural models, which are key elements of Structural Equation Modeling (Little & Kline, 2016). Therefore, MDS can be considered valuable, especially through combination with other already entrenched methods in the field of IS research to enrich a methodological diversity (Venkatesh et al., 2013).

5 Conclusion

Following a phenomenological perspective on technology use by healthcare professionals, this paper introduces explorative MDS as a method to gain insights on contextual factors (or dimensions) constituting a wide range of explanatory power concerning generalizing models. While MDS is compared to other research methods in the field of IS, its comparability and integrability is demonstrated. As the scope of this paper and the illustration of

MDS is limited to its explorative approach, different issues have to be addressed by future research. Therefore, an analysis of hierarchical sorting data of PCPs and PCSs' assistants from an online survey by using Unfolding Models is considered a possible next step to demonstrate the practical application of MDS.

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