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What Other Factors Might Impact Building Trust in Government Decisions Based on Decision Support Systems, Except for Transparency and Explainability?

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Abstract

Decision Support Systems (DSS) are increasingly being used to support operational decision-making using large amounts of data. One key aspect to successful adoption is that the user trusts the DSS. Large contributors to trust often mentioned in literature and practice are transparency and explainability. But what happens when a DSS is transparent and explainable by design? What other contributors to trust are relevant is the main focus of this paper, in the context of Dutch governmental subject-matter experts designing and working with DSSs. We used a Mixed-Method Sequential Explanatory Design in which a survey was conducted to gather empirical data. The findings present 20 focal points contributing toward trust in DSS. These focal points require future research, specifically on considering these for development by the design of a DSS. Ultimately, this could help in increasing the adoption of DSSs in general.

Keywords: Decision Support Systems, Explainability, Transparency, Trust, XAI.

1. Introduction

Decision support technologies, and more specifically, decision support systems (DSS), are subject to extensive research attention (Arnott & Pervan, 2005, 2014). DSSs can be defined as the area of the information systems (IS) discipline that focuses on supporting and improving decision-making (hereafter: DM) (Arnott & Pervan, 2005), both on strategic and operational DM. In this paper, we focus on operational DM as this represents the day-to-day processing of data to solve cases from users. Different types of DSS exist as presented by Arnott and Pervan (2014). This study focusses on the Intelligent Decision Support Systems as a type of DSS, also referred as IDSS (hereafter mentioned as DSS). This type of DSS applies Artificial Intelligence (AI) techniques for the support of decisions. This DSS could again be divided into two generations, where the first generation is a rule-based expert system and the second generation uses neural networks, genetic algorithms, and fuzzy logic (Turban et al., 2005). The focus of this study lies on the rule-based expert systems, which are frequently used in the governmental domain. The practical relevance of a DSS (regarding all DM) lies in the quality of a DM process, which translates to the question of whether a human is supported properly by a DSS. Proper support by a DSS can be beneficial for human DM because of the limited cognitive ability of humans when assessing a wide range of different types of conditions in order to make the right decision, the time available when making these decisions, and the difficulty of the problem requiring a decision (Simon, 1955). These limitations can be summarized under the concept of 'Bounded Rationality' (Simon, 1955). Additionally, a human decision-maker searches through the available alternatives until an acceptable conclusion to that decision is found. By this account, the decision-maker selects the first conclusion that meets the most criteria rather than the 'optimal' solution. This concept is referred to as 'Satisficing' (Simon, 1956) and in combination with 'Bounded Rationality' (Simon, 1955) shows the added value of how and where a DSS could help a human mitigate these aspects and support their DM. Possible problems when not or insufficiently supporting a DM process could result in inconsistent DM or low-quality DM (Blenko et al., 2010).

The acceptance and adoption of technology is a research and industry on its own (Chau, 1996; Holden & Karsh, 2010; King & He, 2006; Lederer et al., 2000; Lee et al., 2003; Marangunić & Granić, 2015; Venkatesh & Davis, 2000). This field focuses on research and practice on what a human requires to accept and adopt the technology. A DSS is characterized as such a technology. Because a DSS supports the DM process, the system itself becomes

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part of the DM process and is thereby confronted with laws (California Consumer Privacy Act, 2018; European Union, 2016), regulations, and principles (Responsible Data Science Initiative, 2016; Wilkinson et al., 2016) related to decisions and DM. These external variables (external variables as stated in technology acceptance research (Chau, 1996; Holden & Karsh, 2010; King & He, 2006; Lederer et al., 2000; Lee et al., 2003; Marangunić & Granić, 2015; Venkatesh & Davis, 2000), could influence the acceptance and adoption of such a system.

To adhere to these laws and regulations, a DSS, amongst other legal aspects, should be transparent and explainable. Transparency (Turilli & Floridi, 2009) and explainability (Guidotti et al., 2019) in technology are thoroughly researched topics. For example, eXplainable Artificial Intelligence (XAI) is the research field focused on transparent and explainable systems (Gunning, 2019). Transparency and explainability are defined in several ways, which is not the focus of this paper.

One industry that focuses heavily on compliance with laws and regulations is the government. For example, governmental institutions in the Netherlands are expected to set a good example for other industries by leading by example (Leiden University, 2017). This is not always adhered to, leading to increased backlash (Clifford Change, 2022). Generally speaking, this is similar in other countries.

Governmental institutions aim to gain trust by providing transparency and increasing the explainability of their DM. We argue that a lot of research attention has been focused on both transparency and explainability, while trust is a concept that is much broader and involves other important focal points as well. Research also shows that each group of stakeholders trust systems differently, their confidence is based upon what and when specific information is disclosed, and how clear, accurate, and relevant the stakeholders perceive specific information (Schnackenberg & Tomlinson, 2016).

This leads us to the direction that focal points other than transparency and explainability need to be explored. The selection of the participants should be based on the group of individuals, organizations, information technology, or community that best represents the phenomenon studied (Corbin & Strauss, 1990). In the context of this study, this means that the phenomenon studied is represented by organizations and individuals within these organizations which design and/or use rule-based DSS. A good example of such an organization would be governmental organizations. Therefore, we conduct this study in the context of the Dutch government, specifically focusing on employees working at Dutch governmental Institutions that design and work with DSSs. In this paper, we focus on human-computer trust, specifically, end-user-computer trust as a relationship. To the knowledge of the authors, this has not been done before in this particular context. Identifying other focal points attributing to trust can be beneficial for the proper design of DSSs overall. To do so, we aim to answer the following research question: *What focal points other than transparency and explainability for a governmental DSS in a Dutch context can be identified that affect trust in DSS?*

The remainder of the paper is structured as follows. First, we define the problem space of DM and the impact of transparency, explainability and trust in the background and related work section. This is followed by the research method used to conduct this study. Then, the way in which the data is collected and analyzed is discussed. Based on our research the results are presented, followed by the discussion, conclusions, and future research directions.

2. Background and Related Works

Transparency and explainability are focal points that go hand in hand in XAI literature (Adadi & Berrada, 2018; Barredo Arrieta et al., 2020; Hagras, 2018; Wachter et al., 2017). Different interpretations, types and definitions of transparency and explainability exist. One of the issues that hinders a clear common ground on explainability is the interchangeable misuse of explainability and interpretability (Barredo Arrieta et al., 2020). The difference here lies in the passive (interpretability) and active (explainability) characteristics of a system with the intent of clarifying or detailing its internal functions (Barredo Arrieta et al., 2020). Because of the active characteristics of a system to clarify or detail its internal functions, the internal functions need to be explainable. Different studies are aiming towards explaining the different functions of a system (AI) (Adadi & Berrada, 2018; Arya et al., 2019; Gilpin et al., 2018; Ras et al., 2022). Explainability is twofold, the system can be explainable, but the target audience perceives a system as explainable or not. Therefore, proper knowledge about the expectations of the target audience is essential. Because different stakeholders, with different levels of expertise, have different needs for an explainable system (Arya et al., 2019). For example, a system could explain its internal functions through a graphical modelling language like the Decision Model and Notation (DMN) (Object Management Group, 2019) or other techniques (Arya et al., 2019), but it is necessary for the explainability to the target audience that they understand DMN or the modelling language used by design. The fact that a system focuses on active functions with the intent of clarifying or detailing its internal functions is not enough, the ability to observe is just as important.

Transparency concerns are usually driven by the logic that the possibility of observing (a system) produces insights, which in turn creates the knowledge required to govern and hold someone or something (e.g. a system) accountable (Ananny & Crawford, 2018). The possibility of observation is broad and thereby gives room to different types of transparency. On the spectrum of clear and non-clear transparency are "fuzzy" transparency versus "clear" transparency different ways to specify transparency (Fox, 2007). Fuzzy transparency is the offering of *"information that does not reveal how institutions behave in practice, or which is revealed but turns out to be unreliable"* (Fox, 2007). Clear transparency are *"programs that reveal reliable information about institutional performance, specifying officials' responsibilities as well as where public funds go"* (Fox, 2007). Moving to transparency and the relation to accountability is where transparency creates "soft" or "hard" accountability (Fox, 2007). Soft accountability is where organizations justify their actions, and hard accountability is where transparency brings the power to sanction and demand compensation for any harms (in addition to answering for their actions) (Fox, 2007). Transparency can be specified as an event or a process (Heald, 2012). Transparency as an event is where the inputs, outputs, or outcomes define the objects of transparency (Heald, 2012). Transparency as a process is where the organizational rules, regulations, and procedures define the conditions of visibility (Heald, 2012). All the different typologies of transparency specify that different ways of transparency exist but stipulate that full transparency has a more positive note to them. Full transparency has its downsides and can do great harm (Ananny & Crawford, 2018). If full transparency is implemented without a notion of why some parts of a system should be transparent, this transparency could threaten privacy and limit honest use of the system (Schudson, 2015). Another downside of full transparency is that it creates vast quantities of information, and because of that, important information becomes buried (Stohl et al., 2016). Kemper and Kolkman (2018) focus on the actors of the transparent system and state that transparency in a system ensures trust in a system and in turn, creates a non-critical audience of the system.

Transparency and explainability are in turn frequently related in literature to ensure trust (Adadi & Berrada, 2018; Ananny & Crawford, 2018; Siau & Wang, 2018). Several studies state that when a system is transparent and explainable, trust in the system could be ensured (Gilpin et al., 2018; Guidotti et al., 2019; Siau & Wang, 2018). However, this recurring perception that trust could be ensured through the transparency of systems and organizations is not accepted in all research (Albu & Flyverbom, 2019).

Trust (human-computer) is defined as: *"the extent to which a user is confident in, and willing to act on the basis of, the recommendations, actions, and decisions of an artificially intelligent decision aid"* (Madsen & Gregor, 2000). Prior research conceptualizes trust as a multidimensional construct that is composed of a set of trusting beliefs, namely, competence (the ability of a trustee to effectively perform in a specific domain), integrity (adhering to principles generally accepted by a trustor, and benevolence (caring and the motivation to act in the trustor's interests) (Mayer et al., 1995; McKnight et al., 2016; Vance et al., 2008; Wang & Benbasat, 2007, 2016; Zahedi & Song, 2008). The scope of this research is towards designing proper DSS, thereby the researchers focus on the competence dimension. Because of this, the literature introduced in this paper is mostly center around enabling and supporting users to effectively perform in a specific domain. Trust in a system comprises multiple perspectives. One perspective, is that different stakeholders of a system could trust a system differently, with their confidence depending on whether the information is disclosed or not, and how relevant, accurate, and clear these stakeholders perceive this information (Schnackenberg & Tomlinson, 2016). Another viewpoint of trust is that of the designers of a system. The designers can possibly not trust the users of a system by providing them with detailed information related to internal functions of the system, e.g., internal fraud detection rules. Transparency and explainability are not the only attributes that contributes to trust in a system. XAI literature is rich with other focal points important to system design, acceptance, and use. For example, focal points like accuracy, interpretability, and accountability are frequently mentioned in XAI literature and linked to transparency and explainability.

Accuracy is to which extent a system could predict instances close to the quantity being measured (Guidotti et al., 2019; Han et al., 2011; Kantardzic, 2011; Tan et al., 2001).

Interpretability is to which extent a system is human understandable (Adadi & Berrada, 2018; Arya et al., 2019; Barredo Arrieta et al., 2020; Burrell, 2016; Doshi-Velez & Kim, 2017; Hagras, 2018; Lipton, 2018; Ribeiro et al., 2016).

Accountability focuses on whom can be held accountable if a system does or does not do something with the effect of e.g. material damage or physical damage (Dwivedi et al., 2021; Wachter et al., 2017).

The body of knowledge claims that trust, and thereby the acceptance and use of a system, is different with each group of stakeholders (Schnackenberg & Tomlinson, 2016) and the primary reason a system is accepted (Gefen et al., 2003).

The insights regarding transparency and explainability from the current body of knowledge are utilized for the construction of 1) the construction of the survey and 2) the construction of the example DSS featuring transparency and explainability by design.

3. Research method

This study aims to explore possible focal points that contribute toward trust regarding a DSS. Therefore, a Mixed-Method Sequential Explanatory Design (Creswell et al., 2003) is selected to be the best fit for reaching this goal, as shown in Figure 1. The research is executed using two phases.

In the first phase, a survey was used to quantitatively provide insights into the opinions of Subject-Matter Experts (SMEs) working at Dutch governmental institutions towards transparent and explainable DSS and trust in a DSS.

In the second phase, two qualitative focus groups were conducted with the goal to detail what focal points are important contributors to trust in a DSS. We focused these discussions by using a demonstration of a DSS developed by the research team that can be characterized by a focus on transparency and explainability by design. Although it is not the main objective of the study, the constructed DSS will be described in more detail in the result section. By using the DSS with this specific focus during the focus groups we can see what other focal points are relevant for trust in DSS among this particular stakeholder group, being Dutch governmental institution employees.

4. Data collection and analysis

The data collection occurred during a conference for Dutch governmental DSS SMEs in April 2022 referred to as the Business Rules Management Conference. In total 56 SMEs were present. The participants have a background in the field of Decision Management, Business Rules Management, Decision Support Systems and Expert Systems. These SMEs analyze business decisions and rules, design decisioning systems, and draft business rules on a daily basis. During this conference, a sample of these participants was involved in phase one and phase two of this study.

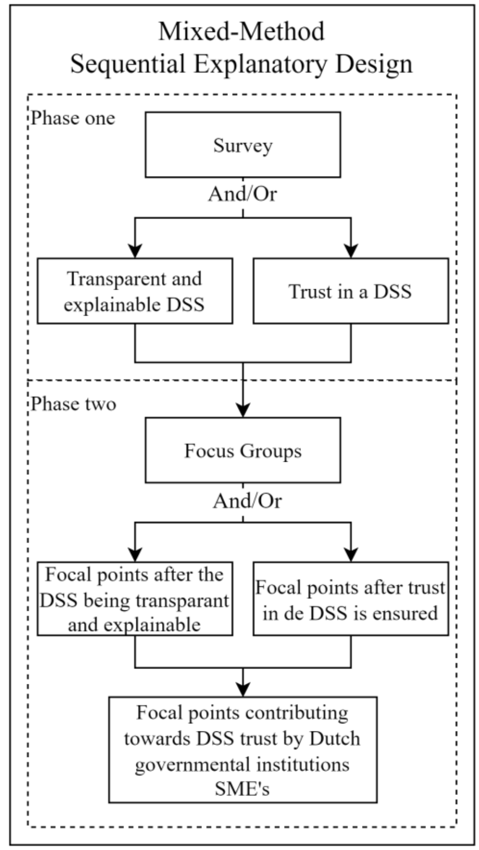

Figure 1 Mixed-Method Sequential Explanatory Design

Phase one

In phase one, *n*=42 participants were involved in a survey focused on collecting the opinions of SMEs towards transparent and explainable DSS and trust in a DSS. The outcome of the survey was analyzed, and descriptive statistics provide the input for the subject of the qualitative focus groups in phase two. The following statements and questions were posed in the survey:

The concepts from XAI literature were utilized to construct seven survey questions. Literature states that trust, and thereby acceptance and use of a system, is different with each group of stakeholders (Schnackenberg & Tomlinson, 2016) and the primary reason a system is accepted (Gefen et al., 2003). The questions used in the survey are detailed in the next section to improve the readability of the results.

A five-point Likert scale is utilized in the survey, which offers a universal method of collecting data known to participants that makes it easy to understand the questions. An even-numbered Likert scale is avoided to avoid neutral answering (Bertram, 2007).

Phase two

The focus of these FGs is to see what other focal points are relevant for trust in DSSs among this particular stakeholder group when a DSS is transparent and explainable. To be able to do so, the researchers demonstrated a DSS (Transparency focal point) and explained the DSS through a presentation (Explainability focal point). The presentation consisted of a slide set containing an explanation of the concepts of a DSS (input data, training data, user interface, and output data) and the modelling language used for the decision models (DMN). The DSS utilized in this study was an example of a rule-based DSS, which are frequently used in the Dutch government. The demonstration entailed discovering a DMN from structured data aimed toward using the DMN in a DM process supported by a DSS. The creation of the DMN is based upon analytical and numerical models and thereby the DMN is explaining any underlying analytical and numerical models. Visual notations such as DMN are frequently used by governmental employees in the Dutch context to model decisions and configure DSS.

After the demonstration and presentation, the FG participants were tasked with providing additional focal points related to their own practical experiences. The focus groups were conducted in two separate rounds. Round one consisted of 11 participants and round two consisted of 9 participants. Participants were not able to join both rounds, resulting in a total of 20 FG participants. The researchers utilized a focus group protocol to ensure construct validity over the different focus groups (McQuarrie & Krueger, 1989). This focus group protocol contained a series of instructions about what should be explained during the presentation and which functionalities should be shown during the demonstration. Additionally, instructions were included regarding the topics that were to be discussed with the participants to derive relevant focal points.

The results of these focus groups were analyzed through thematic coding (Gibbs, 2007) employing multiple coding rounds, being Open coding, Axial coding, and Selective coding. These rounds are adopted from the Grounded Theory approach, which add to the validity and reliability of the structuring of data towards the focal points and categories identified. However, we do not claim to use the full Grounded Theory approach in this study.

Generally, during the open coding round, researchers code ‘’codable observations’’ (Boyatzis, 1998). This was not the case in this study because the researchers instructed the participants with writing down additional focal points related to their own practical experiences. The coding process was conducted by two coders who coded separately from each other. After each round, the coders discussed the codes. To consolidate the codes, disagreements from the separate coding rounds were discussed and a final coding was made based on the discussion.

Open coding of FG round one resulted in 24 unique focal points whereas FG round two resulted in 13 unique focal points. During the second round of axial coding, the two coders collaborated in defining and coding the focal point. The axial coding round resulted in the coding of 20 unique focal points.

The third and last round of selective coding focused on coding focal point main themes. The coders identified two focal point themes after analyzing the focal points. These main focal point themes were: 1) Concerns and 2) Benefits. Disagreement between the coders in the third round occurred seven times and after discussing the disagreed upon codes, the coders concluded with coding 16 Concerns and 4 Benefits.

The focal point theme Concerns is coded when a participant mentions something about a DSS when this is a threat to adoption. The focal point Benefit is coded when a participant mentions something about the DSS when this is a possible Benefit of using the DSS in the context of the participant.

5. Results

Phase one

From the analysis of the results of the survey could be differentiated that the participants lean towards the importance of trusting a DSS when it is transparent and explainable or instead trusting a DSS without it being transparent and explainable by design, as shown in Figure 2. The following questions were used in the survey:

- Q1: The validity of the outcome of a decision support system is more important than if a system is transparent and explainable
- Q2: If a decision support system is transparent and explainable, I trust the system
- Q3: I will use a decision support system if it is transparent and explainable
- Q4: I trust the decision-maker when I trust the decision support system
- Q5: How important do I think transparency is in a decision support system?

- Q6: How important do I find explainability in a decision support system?
- Q7: How important do I think trust in the outcome of a decision support system is?

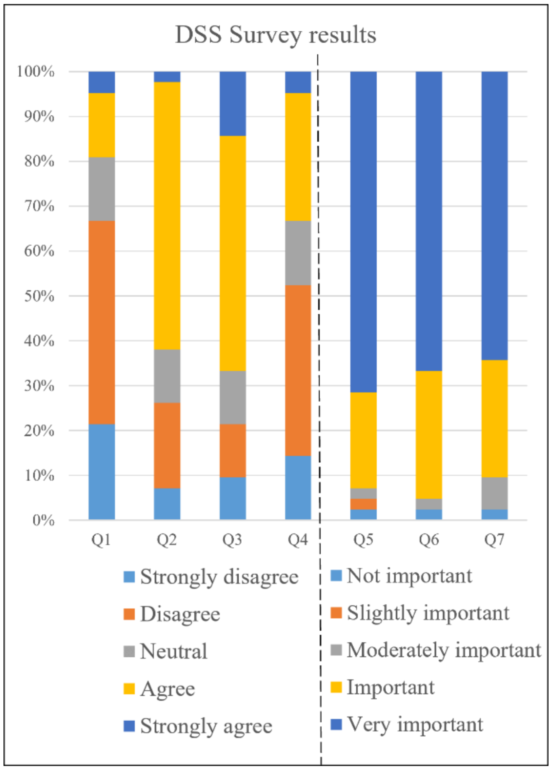

Figure 2 DSS Survey results

The results of phase one were indicative for the demonstration and presentation (phase two) to see whether it should focus on trust without transparency and explainability or solely focus on transparency and explainability.

Phase two

After the coding of the outcomes from the focus groups, focal points and overarching focal point themes were identified. The Axial coding round resulted in 20 unique focal points and the selective coding round resulted in the coding of 2 overarching focal point themes. The two focal point themes were 1) Benefits and 2) Concerns. The focal point theme Benefits is coded 4 times, and the focal point theme Concerns is coded 16 times, as shown in Figure 3.

We define all coded focal points in this sub-section. However, due to space constraints, not all focal points are accompanied by an example from the data.

Concerns

Representability

The focal point *Representability* concerns that when the input data and training data is seen as the ‘truth’, the resulting model (e.g., DMN) could be incomplete because rules not present in the data are not incorporated by the DSS. An example of the observation leading to the coding of Representability is as follows: *“The first data set is the 'truth' if the system is data driven. Business rules versus implementation practice may not be the same”*.

Model Interpretability

The focal point *Model interpretability* concerns that the resulting model (e.g., DMN) can be hard to interpret for SMEs due to them not always knowing the scope of the data used for creating the DMN. An example of the observation leading to the coding of Model interpretability is as follows: *“The scope of the data used for the decision model is not clear”*.

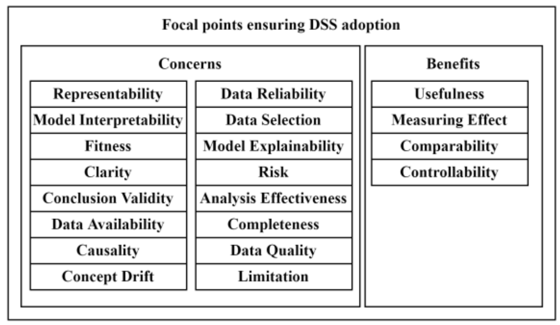

Figure 3 Focal points contributing towards trust in DSSs

Fitness

The focal point *Fitness* concerns that the dataset used for the creation of a DMN is not large enough and misses possible decision instances to be representable when seen as the “truth”.

Clarity

The focal point *Clarity* concerns that it should be clear what the input data, training data, DSS, and output data and DMNs entails and is used for.

Conclusion Validity

The focal point *Conclusion Validity* concerns the possibility that exists when the outcome is different than expected from the initial input data. Therefore, the conclusion could not be valid with law- and regulations.

Data Availability

The focal point *Data Availability* concerns that data must be available in order to result in reliable conclusions by the DSS. Participants stated that data required for DM is not always fully available and one could either choose to continue the decision or wait until all data is available, depending on the situation.

Causality

The focal point *Causality* concerns that a DMN could represent something that is untruthful. For example, that there is a relation between variables in a decision model but there is no actual causality between the variables.

Completeness

The focal point *Completeness* concerns the question whether the data and the variables that represent it is enough for DM. For example, whether a dataset is representable over a certain time period.

Data Quality

The focal point *Data Quality* concerns the fact that the quality of the input data could be ambiguous, inconsistent or inaccurate. This leads to lower quality DM.

Data Reliability

The focal point *Data Reliability* concerns a comparable explanation as *Data quality,* but it is more specific to when the data is available for the DSS and decision-makers to consider during DM.

Data Selection

The focal point *Data Selection* concerns what dataset should be selected as input data and training data. The governmental employees stipulated that they had some concerns on which dataset should be selected as input data as they are not always known with the origins of the datasets.

Model Explainability

The focal point *Model Explainability* concerns the explainability of the DMN used in the DSS. This explainability was more focused to the explainability of the DMN and not specifically explaining laws and regulations in the context of the governmental institutions. The specific governmental institutions represented at the focus groups focus on executing laws and regulations. Because of their DSS being driven by law and regulations, they favor explainability of the law and regulations as well, also because these organizations are responsible for translating law and regulations into DMN or other DSS-proof languages.

Risk

The focal point *Risk* concerns the overarching risk the governmental employees observed when, for example, input data is used to create a model. The risk was related to the possibility that truth could be spread by data, while this is not always guaranteed to be reliable enough for DM. This same argument could hold for the utilization of training data.

Analysis Effectiveness

The focal point *Analysis Effectiveness* concerns that it should be clear what specific question should be asked to a dataset or DMN in order to actually be useful in a DSS and DM process.

Limitation

The focal point *Limitation* concerns that the DSS used is only able to interpret structured data, while many datasets used in practice are unstructured. An example of the observations leading to the coding of Limitations is as follows: *"Unstructured data part of decision making is common"* and *"Structured data is often not available".*

Concept Drift

The focal point *Concept Drift* concerns that laws and regulations could change over time and that this is not visible in the data. This leads to complex DM when data over longer periods is required.

Benefits

Usefulness

The focal point *Usefulness* concerns the perceived usefulness by SMEs and strongly affects the trust in the DSS. An example of the observation leading to the coding of the focal point *Usefulness* is as follows: *"More insight into the quality of the decisions taken. This can help prevent incorrect decisions"*.

Measuring Effect

The focal point *Measuring Effect* concerns that SMEs want to measure the effects of law and regulations on the actual implementation in practice by DSSs. An example of the observation leading to the coding of Measuring effect is as follows: *"Related to policy effects the intended goal can be compared with the realized goal".*

Comparability

The focal point *Comparability* concerns that the outcome of a DSS could be compared to another outcome of a DSS and through this comparison, insights could be achieved in order to improve a DSS and the DM process.

Controllability

The focal point *Controllability* concerns that rules that are created before the implementation in a DSS can be verified and validated whether the decisions and rules are correct and implementable.

6. Discussion

The findings in this study have to be seen in the light of some limitations. The first limitation concerns the method utilized in this study. Although we argue that a Mixed-Method Sequential Explanatory Design allowed us to answer our research question, one could question the fit of the combination of methods utilized in the context of this study as a combination of different methods could have yielded different results.

Another limitation could be seen in the coding, which is conducted by two researchers. While more coders could have been involved to increase the validity of the results, we argue that the multiple coding rounds have been employed as well as that the coders have a strong background in coding qualitative research data along with the research domain at hand. The coding rounds have been conducted separately and discussed afterwards to consolidate the results.

One of the strengths and main contributions of the study is also a possible limitation towards its generalizability. Concerning the participants, one could argue that those included in this study are looking differently towards the aspects of transparency, explainability, and trust compared to users that do not have a background in DSSs but are merely end-users. While we agree that this could be a possible bias, it also offers a unique view of the problem space addressed. Furthermore, the participants are all SMEs in their field and are well known, next to their perceptions, with how their users perceive (public services based on) DSSs as their main task is to design and deliver such systems that can be trusted. Therefore, future research should include a more diverse group of participants from within the governmental domain, which is then compared towards other industries to reflect on the possible differences in focal points between them. This would increase the generalizability substantially.

The choice for not focusing on one specific DSS could be seen as a limitation. Although the focus of this study lies on the transparency and explainability of the DSS capabilities. Selecting one or multiple DSS solutions would possibly help the participants in generating focal points when confronted with, for example, popular DSS in the Dutch governmental domain like: ALEF (Dutch Tax and Customs Administration, 2022), RuleXpress (RuleArts, 2022), ODM (previously JRules) (IBM Corporation, 2022) or BeInformed (BeInformed, 2022). Besides the focus on a different DSS, future research could also extent existing DSS (used in the governmental domain) with anthropomorphism and social presence capabilities. In IS research, a social relationship perspective is often applied, which examines the role of anthropomorphism and social presence in determining trust and acceptance of decision support technologies (e.g., (Qiu & Benbasat, 2009)).

The goal of our approach was to exclude both transparency and explainability in such a way that all other focal points contributing to trust could be explored. While this is an approach that fits the novelty of examining perceptions in this context, it could be the case that by using this approach we unintentionally gave less known or obvious focal points less attention, which possibly affects the completeness of the list with focal points. An approach to mitigate this is to provide participants with the full spectrum of focal points that are known to contribute toward trust in DSSs with the goal to prioritize and detail them further.

Lastly, the results of the survey indicate that the utilization of non-transparent and non-explainable techniques (e.g., Neural networks or Support Vector Machines) in a DSS would result into the DSS not being accepted and thereby not (adequately) used by the participants involved in this study (the participants being Dutch governmental employees). Future research should focus on whether this is the case solely for Dutch governmental employees compared to other governmental employees outside of this context.

7. Conclusion

To conclude this study, we revisit the research question posed in the introduction section: *What focal points other than transparency and explainability for a governmental DSS in a Dutch governmental context can be identified that affect trust in DDS?*

Based on the analysis of the results from both phases, which employed a survey and two focus groups, a total of 20 focal points were identified that affect trust in a DSS, of which an overview is presented in figure 3. Overall, we observed that concerns are often mentioned, while the benefits are posed less by the participants. Concern-type focal points are also observed to be more often unique compared to the Benefit-type focal points. Both observations show that many participants included in this study reason from concerns easily, while the benefits seem to be harder to imagine, given the demonstration provided in the focus groups.

Another conclusion that can be drawn from this study is that the approach used for excluding focal points seems successful with regard to the transparency and explainability of DSSs.

From a theoretical perspective, this study contributes by creating new knowledge on the design of DSSs in the context of Dutch governmental SMEs and provides a fundament for future research directions. The results show that future research is required into whether the current set of focal points provides a near-complete overview of contributors to trust for DSSs as well as into what mechanisms and functionalities within these focal points can be used to further increase trust in DSSs.

From a practical perspective, this study contributes by giving insight into focal points other than the commonly used transparency and explainability that contribute toward trust in a DSS.

The results help in developing DSSs that are easier to trust, because important focal points are, by design, taken into consideration. This becomes increasingly important as an increasing number of government services are transformed from analogue 'physical' processes and services into (fully) digitized systems.

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