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Future Challenges in Decision Mining at Governmental Institutions

Completed Research

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Abstract

Decisions are made in fast-changing situations. To cope with this, decision mining could be utilized to support the decision-making process. Decision mining is an emerging field which could support an organizations decision-making process. For proper utilization of decision mining, possible challenges should be identified to take into account when mining decisions. As such, two focus groups were conducted where we identified 11 main challenges that seven Dutch governmental institutions deemed important and which should be taken into consideration when mining decisions. The identified challenges are depicted further together with existing literature and the coded observations. The identified challenges could be utilized as future research directions and are discussed as such.

Keywords

Decision mining, challenges, focus groups, governmental institutions

Introduction

Decisions are made in fast-changing, sometimes unexpected, situations (Smirnov et al. 2009). Such situations require the right decision maker and supplying the decision maker with the correct data. Decision mining could support in solving this problem by estimating data quality and interpreting their semantics and relevance, the interpretation of the actual meaning, and unit of measurement (Smirnov et al. 2009). Another advantage is the classification of decisions, which allow the discovery of correspondence between decision makers and their roles through the development of decision models and (semi) automatic decision analysis techniques (Smirnov et al. 2009). Decision mining is defined as: *“the method of extracting and analyzing decision logs with the aim to extract information from such decision logs for the creation of business rules, to check compliance to business rules and regulations, and to present performance information”* (Leewis et al. 2020). Decision mining can be segmented into three activities (Leewis et al. 2020): Discovery, Conformance checking, and Improvement. The decision mining activities support decision-making by utilizing and supporting existing information system data structures. Decision mining utilizes structured data from information systems which are involved in a decision-making process.

Previous decision mining research state that a specific focus is needed to further grow the decision mining research field (Leewis et al. 2020; Sarno et al. 2013; De Smedt, vanden Broucke, et al. 2017). Current decision mining techniques focusses lack the capacity to deal with logbooks containing deviating behavior, lack the capacity when dealing with complex control-flow constructs (de Leoni and Van der Aalst 2013),

and lack a holistic overview of the decision model (De Smedt, vanden Broucke, et al. 2017). Recent research is focused on a more holistic discovery of decisions (De Smedt, Hasić, et al. 2017), however, this is still conducted from a business process viewpoint perspective and where event logs are utilized as input data. Future research should focus on decision mining techniques which could actually handle complex control-flow constructs and have a decision point of view (Leewis et al. 2020).

Ensuring that newly created decision mining techniques and methods are based on actual real-world concerns or challenges, these challenges need to be identified. To the knowledge of the authors, no research exists where decision mining challenges are identified. Currently, a broad spectrum exists on challenges and critical success factors of fields related close to decision mining. Research fields related to decision mining are, for example, process mining (Van der Aalst 2011) and data mining (Han et al. 2011). Che, Safran, and Peng (2013) focus on challenges relating data mining and big data concerning heterogeneity, scale, speed, accuracy and trust, privacy crisis, interactiveness, and garbage mining. Other data mining research focusses on challenges related to the credit industry (Olecka 2007). Olecka (2007) identified challenges concerning the risk of unbalanced datasets, broad definition of targets, segmentation, and combining data. Van der Aalst et al. (2012) identified challenges relating to the utilization of process mining (Van der Aalst 2011) concerning challenges such as, but not limited to, finding, merging, and cleaning event data, dealing with complex event logs, dealing with complex drift, and usability by non-experts.

Organizations which have a vast amount of historical (decision) data are a perfect fit to utilize decision mining techniques. Governmental institutions are organizations which store (vast amounts of) data of their decision-making, which in turn could be utilized for decision mining. This research is focused on challenges proposed by governmental institution professionals of utilizing decision mining in the future. These professionals are future users of decision mining and could indicate possible challenges of utilizing decision mining. Therefore, their concerns (challenges) are identified (even when the focus is mainly on the technological, societal or legal challenges), that serve as a basis when creating specific techniques for the Discovery, Conformance checking, and Improvement of decisions, taking into account the identified challenges. To do so, we aim to answer the following research question in this research: *What are the challenges professionals at governmental institutions (may) face when utilizing decision mining?*

The remainder of the paper is structured as follows: First, decision mining and related concepts are further defined. This is followed by the research methods used in this research to identify challenges of decision mining at governmental institutions. Next, the data collection and analysis of this research is discussed. Subsequently, the results section presents the identified challenges. Lastly, we present our conclusions and discuss the used research methods and the results, possible future research directions, and conclude the paper.

Background and Related Work

Decision mining is focused on extracting information from decision logs (discovery), check this information for compliance with business rules and regulations (conformance), and present possible performance information (improvement), as depicted in Figure 1. The decision mining activities are comparable to the more mature field of Process mining (Van der Aalst 2011).

Discovering patterns, Checking on conformance, and proposing Improvement are no unique steps when dealing with the identification of patterns in general (Van der Aalst 2011; Han et al. 2011). When research aims to extend existing solutions to tackle new problems Hevner and Gregor (2013) state that these known solutions can be adopted from related research fields data mining (Han et al. 2011) and process mining (Van der Aalst 2011) identified by Leewis et al. (2020).

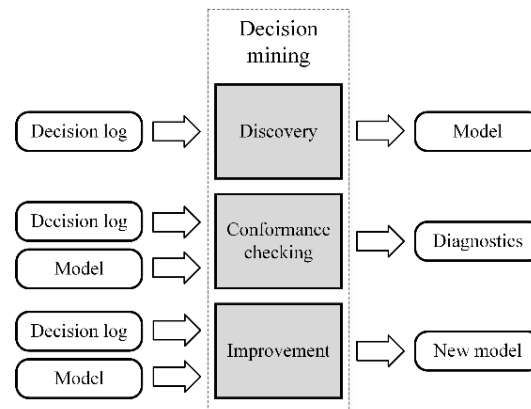


Figure 1 Decision mining activities (Van der Aalst 2011; Leewis et al. 2020; De Smedt, vanden Broucke, et al. 2017)

Research Methods

In this explorative research, we identify challenges that professionals at governmental institutions could encounter when mining decisions. The maturity of the decision mining research field is identified as nascent (Leewis et al. 2020; Sarno et al. 2013; De Smedt, vanden Broucke, et al. 2017). When a research field is in a nascent state, new constructs should be identified and relations between these constructs should be established (Edmondson and Mcmanus 2007). To do so, we utilize explorative qualitative research methods. Due to the nascent state of the research field, decision mining, as defined in this study, is not mature enough to apply a selection of the decision mining activities (Discovery, Conformance checking or Improvement). Therefore, the domain expertise of professionals is utilized to depict some possible challenges when these professionals use decision mining in their domain in the future. To the knowledge of the authors, no research exists where decision mining techniques take into account previous identified challenges or requirements. Through grounded theory, we search for possible challenges which are expected by professionals when, in the future, decision mining is used. A wide range of research methods are adequate when exploring a broad spectrum of complex challenges related to a complex topic and combine them into representative categories when a lack of empirical evidence exists. Group based research methods would facilitate this (Delbecq and Van de Ven 1971). One type of group-based research methods are focus groups, which can be utilized for data collection or validation purposes. In this research, focus groups are conducted for the purpose of data collection. During these focus groups, participants have the possibility to broadly interact on a topic in a limited amount of time.

Data Collection & Analysis

The data collection took place during a Business Rules Management (BRM) and Decision Management conference of the Dutch government on November 22nd, 2019. Several topics need to be addressed before a focus group can be conducted: 1) the goal of the focus group, 2) the participants, 3) the number of participants, 4) the facilitator, 5) the information-recording facilities, and 6) the focus group protocol (Morgan 1997). The participants of the focus groups (and conference) are people responsible for the translation of legislation into decisions in information systems. Important for this is the feedback loop on the decisions made which could be conducted by mining techniques, currently performed in business intelligence solutions, manually, and ad-hoc. Participants of the conference are all BRM and Decision Management professionals that joined voluntarily, which addresses the participant selection criterion for a focus group. Employees from Dutch governmental institutions (as shown in Table 1) were present during two separate focus group (focus group one and two) rounds and thereby providing input for this research. The two focus groups consisted of a total of 33 applicants from seven Dutch governmental institutions of which 17 participants in focus group one and 16 participants in focus group two. Participants in focus group one did not participate in focus group two and vice versa.

Organization ID:	Governmental institution:	Focus group #:
A	Dutch Social Security Office	1
B	Dutch Employee Insurance Agency	1
C	Dutch Tax and Customs Administration	1
D	Dutch Food and Consumer Product Safety Authority	1
C	Dutch Tax and Customs Administration	2
B	Dutch Employee Insurance Agency	2
E	Dutch Immigration and Naturalization Service	2
F	Dutch Education Executive Agency, Ministry of Education, Culture and Science	2
G	Ministry of Finance	2

Table 1 Focus group participants

The facilitator of the focus group has seven years of research experience in the research fields of BRM and Decision Management and has facilitated similar focus group meetings in the past. The focus group participants wrote their challenges on post-its and sheets of paper. The two focus groups lasted for one hour each. The two focus groups followed the same protocol: 1) starting with an introduction and explanation of the goal and procedures of the meeting, 2) the participants generated challenges, 3) the participants shared and discussed their challenges, and 4) the focus group came to a consensus which challenges are relevant after presenting the challenges.

Grounded theory

The data analysis is conducted utilizing the grounded theory process of Corbin and Strauss (1990). This process consists of 1) open coding, 2) axial coding, and 3) selective coding. The coding was conducted by two separate coders. After the separate coding the coders discussed the output of the coding on agreement or disagreement, thereby improving the inter-rater reliability of coding (Tinsley and Weiss 2000) and the internal validity of this study (Reis and Judd 2014). After the two focus groups, the researchers conducted open coding. Generally, during the open coding round, researchers code “codable observations” (Boyatzis 1998). This was not the case in this study. The researchers explicitly asked decision mining challenges from the participants, thereby only challenges were written down and collected. Subsequently, this approach leaves out possible interpretations of the researchers at the open coding round. One of the observations was: “*Decision mining is logbook dependent*”, as shown in Table 2. Subsequently, we conducted axial coding where the researchers each coded challenge to a category, as shown in Table 2.

Challenge ID:	Organization:	Challenge:	Axial coding:	Selective coding:
4	A	Decision mining seems logbook dependent	Data dependency	Input data

Table 2 Coding example

The last round of the grounded theory coding process is selective coding. The researchers categorize the identified challenges, through inductive reasoning, that were produced by the previous axial coding round. The researchers utilized inductive reasoning to reason from specific challenge categories to general challenge categories. This resulted in the coding of *Data dependency* into the general coding category of *Input data*, as shown in Table 2.

Results

In this section, we list the identified challenges as a result of the ground theory process. The order of the challenges does not represent the importance or relevancy of the challenges. The notation used for a (sub) challenge is shown as follows: *Challenge* or *Sub-challenge*. The notation used for an observation which led to the coding of the (sub)challenge is as follows: “*observation*”. The identified challenges are reported together with examples of observations which led to the coding of the challenge and existing

literature that matches the observation, thereby theoretically grounding the identified challenges (Goldkuhl and Cronholm 2010). If the identified challenges are relatable to related fields of decision mining, the challenge is supported with existing literature from related fields. If this is not possible, the concepts are discussed with existing literature to the concept discussed in that challenge. Besides being directly related to literature, a challenge could be a notion of worry from participants, based on their experience in their field. This is described the same as other challenges for these could be used, as of the other challenges, for future research and design guidelines for decision mining techniques.

Challenge #1: Input data

Decision logs may have different aspects. On the one hand, there are decision logs that are large, which makes it difficult for the performance of algorithms and on the other hand there are small decision logs which makes it difficult to draw reliable conclusions (Deelman and Chervenak 2008). For example, looking at decision log DL1, with one decision, and ten different outcomes with 1000 cases. Decision log DL2 has four decisions but only four different outcomes with 100 cases. The difference between the decision logs is clear and both have a different level of complexity as DL1 only consists of one decision, and thus, no dependencies between decisions, while DL2 consist of multiple dependencies between decisions. The goal is to gather decision logs that consist of the required elements because the efficiency and effectiveness of decision mining relies on the *Data quality* of the input data and is thereby strongly *Dependent* on input data. This goal overlaps with neighboring fields (Van der Aalst, Adriansyah, de Medeiros, et al. 2012).

The quality of the decision log depends on the input data. A decision log contains only sample behavior and decision mining techniques need to deal with incompleteness coherent to this sample behavior. The fact that something is not registered in a decision log does not mean that it cannot happen. Examples of the observations leading to the coding of the *Data quality* sub-challenge are as follows: “*Decision mining should take into account missing values*” (Organization B, ID 37) and “*Data contamination could affect the data quality of decision mining*” (Organization A, ID 24). These observations warn that input data is not always of good quality. On the other hand, decision logs can contain outliers, which can be described as exceptional behavior or called ‘noise’. The challenge is to define and detect these outliers in order to eventually clean the decision log data and increase the data quality. Too much noise that is not removed will blur the decision model. Extracting decision log data suitable for decision mining still requires attention. As the mining of decisions is heavily dependent on gathering data. Examples of the observations which led to the coding of the sub- challenge *Data dependency* are as follows: “*Data availability seems an issue in decisions*” (Organization A, ID 23) and “*Large datasets are needed to cover exceptions*” (Organization C, ID 21). The output of Decision Management Systems (DMSs) are not always consistent and algorithms rely on a structured fixed pattern as input data.

Challenge #2: Output data

The output of decision mining algorithms is another challenge. While the standard used for modelling decisions is the Decision Model and Notation (DMN)(Object Management Group 2019), multiple visualizations are possible, for example, RuleSpeak or RuleXpress (Ross 2003). These languages do not work with decision tables and decisions, but with business rules and a controlled natural language. Decision mining algorithms have to transform the output to these representations and can not only present it as a decision table or simple business rules. This would mean that different algorithms have to be used for the transformation or even completely new developed algorithms to extract these other languages. An example of the observations which led to the coding of the sub-challenge *Understandability* of the Output data are as follows: “*Maintaining the overview and it should be feasible*” (Organization B, ID 9). Maintaining the overview of the output data increases the understandability for the decision mining users. Wrongfully interpreting the decision mining output data could possible negatively affect the decision-making process. Discovery algorithms must warn for low fitness or for overfitting (challenge #6) of data when showing a model. This ties closely to explainability. An example of the observations which led to the coding of the sub-challenge *Explainability* of the Output data are as follows “*If a decision is always overruled, it is possible that the rule is incorrect. You must now ask why*” (Organization E, ID 46). These conclusions can only be drawn if the algorithm output is explainable and set into a understandable explanation (e.g. understandable for people on language level B2).

Challenge #3: Added value

The third challenge is added value. How can decision mining add value to an organization? An example of the observations which led to the coding of the *Added value* challenge are as follows: "What is the added value compared to what we have now?" (Organization B, ID 13) and "From 'customization' to 'sustainable policy'" (Organization F, ID 41) The participants were not clear about the added value compared to the tools they are using right now. The sub-challenges Usability and Implementation further depict the Added value challenge. Increasing the usability and thereby adding value of organization through decision mining is identified as a sub-challenge. An example of the observation which led to the coding of the sub-challenge *Usability* is as follows: "Open norms must be possible" (Organization D, ID 6). Open norms are outcomes of decisions that are not strict. For example, the outcome of a decision can be blue, but with slightly different conditions the outcome can still be blue but could also be purple. This is a challenge because recognizing these open norms can add value to organizations. The implementation of decision mining is also identified as a sub-challenge. When looking at the decision management lifecycle there are two phases (Smit and Zoet 2018). The implementation-independent phase and an implementation-dependent phase. The question an organization must ask is in which of these phases to use decision mining. Is it a validation within the implementation-dependent phase or must it guide back to the implementation-independent phase? An example of the observation which led to the coding of the sub-challenge *Implementation* is as follows: "System dependent or system independent" (Organization A, ID 1). The challenge is to make decision mining usable for every different type of user, with different backgrounds. Representative benchmarks are needed to show the added value of decision mining in accordance with the sub-challenges usability and implementation.

Challenge #4: Traceability

Traceability is becoming more and more important with regulations coming into place to protect citizens like the California Consumer Privacy Act (CCPA) and the General Data Protection Regulation (GDPR) (CCPA 2018; European Union 2016). Traceability and especially software artifact traceability is defined as "The ability to describe and follow the life of an artifact (requirements, code, tests, models, reports, plans, etc.) developed during the software lifecycle in both forward and backward directions" (Gotel and Finkelstein 1994). Examples of the observations which led to the coding of the *Traceability* challenge are as followed: "Signalling, finding the reason of the decisions' outcome" (Organization B, ID11) and "In which cases are payment arrangements made in the event of late payment?" (Organization F, ID 39). Relating this to decisions and decision-making, traceability ensures to find out on what specific ground with which conditions a decision is made.

Challenge #5: Transparency

Transparency is a frequently researched topic related to, for example, artificial intelligence (Hildebrandt 2012; Sloan and Warner 2018; Weller 2019). Achieving highly transparent techniques (utilizing algorithms) a trade-off is needed between transparency and accuracy. Specific techniques are highly accurate but low in transparency (Kamwa et al. 2012). Relating this to decisions and decision-making it is even mentioned in the GDPR, which demands transparency regarding operational decisions that are integrated into organizations business processes (European Union 2016). An example of the observations which led to the challenge *Transparency* is as follows: "How to make implicit decision information explicit?" (Organization C, ID 50). This challenge does not stand on its own. Transparency is related to other challenges in this research (traceability, validity, law, output data, and expert knowledge). For each application of decision mining, a trade-off should be made between accuracy and transparency.

Challenge #6: Fitness

Fitness measures the extent to which the decision models capture the observed behavior as recorded in decision logs, which is comparable to the concept of fitness in process mining, that focusses on process models and event logs (Adriansyah et al. 2011). A (decision) model has a perfect fitness if all possible dependencies can be traced by the (decision) model from beginning to end (Van der Aalst, Adriansyah, and Van Dongen 2012). An example of the observations which led to the coding of the challenge *Fitness* is the

following: “How does decision mining handle exceptions” (Organization E, ID 54). Fitness could be depicted in two elements “underfitting” and “overfitting”. Underfitting is defined as “Models where some parameters or terms that would appear in a correctly specified model are missing either by mistake or by design” (Everitt and Skronidal 2010). Specific for decision mining, the decision model allows for behavior which is different from what is seen in the decision log. Overfitting is defined as “Models that contain more unknown parameters than can be justified by the data” (Everitt and Skronidal 2010). Overfitting for decision mining is that a specific decision model is generated where it is obvious that the decision log only contains a sample. Situations should be identified where underfitting or overfitting are desirable trades of the specific decision mining applications.

Challenge #7: Validity

To be able to use decision mining in (critical) cases, a high degree of validity is required to ensure reliable and generalizable output data. An example of the observations which led to the coding of the general challenge of *Validity* is as follows: “Check on prejudice in decision mining” (Organization C, ID 51). Validity can be separated into internal and external validity. Internal validity is the reliability or accuracy of the results of a study, tool or measurement (Campbell and Stanley 1963). Decision mining has high internal validity when the output data of decision mining is reliable or accurate and thereby ruling out alternative versions of the output data. Examples of observations which led to the coding of the *Internal validity* sub-challenge is as follows: “decision mining should take into account testing and simulation” (Organization C, ID 33) and “a feedback loop for legal purposes should be integrated in decision mining” (Organization A, ID 26). External validity is known in research as the generalizability of the results of a study to a specific population, setting, or variables (Campbell and Stanley 1963). Related to decision mining this means that the output data (decision model, diagnostics, or new model) of decision mining could be generalised to another context. An example of the observations which led to the sub-challenge of *External validity* is as follows: “How is decision mining itself validated” (Organization C, ID 18). High validity can be ensured by utilizing accurate and reliable decision mining techniques (ensuring internal validity), and utilizing a data sample representative towards the population when decision mining (ensuring external validity).

Challenge #8: Expert knowledge

Governmental institutions utilize information systems in their day-to-day operations to facilitate the professionals working at these agencies to increase public value (Moore 1995; Talbot 2011). Professionals who are not subject matter experts should be able to utilize decision mining without requiring any specific training. A wide spectrum of literature shows a difference in actions between experts and non-experts (Arnold et al. 2006; Cheng et al. 2001; Novick 2006; Verdi et al. 2002). Decision mining is an addition to information systems used by governmental institutions professionals in supporting the decision-making process. An example of the observations which led to the *Expert knowledge* challenge is the following: “Certain expertise seems needed to check decision mining operations” (Organization A, ID 27). Stated by participants, specific expert knowledge seems needed for decision mining and the domain it applied in. Further focus seems required to ensure a user-friendly interface where non-experts could use the capabilities of decision mining and thereby not confronted with algorithms where expert interpretation is needed.

Challenge #9: Legal

Legal outfall related to algorithms involved in automated decision-making or algorithms related to privacy and personal data is a topic depicted in the European GDPR or American CCPA (CCPA 2018; European Union 2016). Every organization needs to comply with the GDPR (or CCPA), especially the government which is a forerunner and need to set the right example. Examples of the observations which led to the *Legal* challenge were as follows: “Decision mining should comply with the GDPR legislation” (Organization B, ID 45) and “Decision mining related cases should hold before court” (Organization E, ID 55). Decision mining related technology should be used conform these requirements when involved in automated decision-making or when dealing with personal data.

Challenge #10: Concept drift

In fast changing and dynamic environments, data distribution changes over time resulting into *Concept drift* (Widmer and Kubat 1993). Concept drift refers to conditional changes in the output (i.e., decision model) through changes in the input (decision log), while the distribution of the input may stay unchanged (Gama et al. 2014). For example, when a condition is renamed. This could have the effect of that this renamed condition is detected as a whole new condition, which is untrue because this is only a change of the conditions label. An example of an observation which led to the challenge of *concept drift* is as follows: (Organization E, ID 57) "*How do you prevent confusion between old and new [versions of] business rules which are live and executed simultaneously*". Focus is needed in identifying algorithms which can detect conditional changes compared to algorithms which cannot or do so too late in the decision mining process.

Challenge #11: Cross-organizational

Decision logs serve as input for decision mining and are the data representation of executed decisions (De Smedt, vanden Broucke, et al. 2017). The decision-making process could cover multiple departments but also organizations resulting in separate decision logs across a single organization or multiple organizations. To discover decisions through decision mining the decision logs need to be merged. This is a non-trivial task as decisions need to be correlated across departments or across organizational boundaries. An example of an observation which led to the challenge of *Cross-organizational* is as follows: (Organization E, ID 47) "*Checking if business rules are applied consequently in different organization locations*". Future decision mining technologies should be able to conduct cross-organizational decision mining. Privacy and security issues could arise when conducting cross-organizational decision mining. Sharing information relating to decisions (e.g. different rule patterns) are possibly harmful for organizations and lose their competitive advantage.

Discussion and Conclusion

In this research, we aim to answer the following research question: *What are the challenges professionals at governmental institutions (may) face when utilizing decision mining?* To be able to do so, we conducted two (explorative) focus groups. In total, 33 participants from seven Dutch governmental institutions participated in this research. After collecting and analyzing our data, the researchers identified 11 challenges related to mining decisions in governmental institutions. These challenges should be taken into consideration when mining decisions in an organization.

This research has several limitations one should consider when focussing on the identified challenges. The first limitation concerns the fact that decision mining, as defined in this research, is not used in practice. Decision mining is currently performed in business intelligence solutions, manually, and ad-hoc. Nevertheless, related research fields of decision mining are known and adopted, from this perspective assumptions could be made. To further ground the challenges, one can look to related research fields (process mining or data mining). Hevner and Gregor (2013) state that when research aims to extend known solutions to new problems state that these known solutions can be adopted from related research fields, e.g. data mining (Han et al. 2011) and process mining (Van der Aalst 2011). These are related research fields aiming on mining patterns to support and improving decision-making (Leewis et al. 2020). Related to this limitation is the spread of the topics discussed in the challenges. The spread of challenges is an effect of the open approach of the researchers during the focus groups. Additionally, this field is not fully explored in terms of its applications, which leads to the fact that the challenges look to be spread over different topics.

The second limitation concerns the sampling and sample size. The participants of this research solely came from governmental institutions in the Netherlands. While we believe that governmental institutions are representative towards other organizations where decision mining could be utilized, future research focusses towards non-governmental industries like health-care or finance increases the generalizability. These industries are interesting because of their critical decision-making situations and the potential impact decision mining could have. This same argument holds when looking to other countries, especially with other privacy and personal data legislation. Extending this research to other countries would possibly identify other challenges related to different legislation, or different culture related challenges. With regards

to the sample size, we believe that 33 participants from seven Dutch governmental institutions is a sufficient sample for this explorative research to be generalizable towards the context from which the challenges were drawn. Nevertheless, adhering to the *Fitness* challenge, future research should focus on including more participants, preferably in line with the previous mentioned future research directions. Lastly, relating to previous limitations, this list of challenges is not intended to be complete, overtime new challenges may emerge or existing challenges may disappear due to advances in the decision mining research field. Therefore, future research should take into account these challenges when designing decision mining solutions for governmental institutions (and other types of organizations).

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