DMISTA: Conceptual Data Model for Interactions in Support Ticket Administration

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Abstract: Changing business models and dynamic markets in the globally connected world results in more and more complex system environments. The IT service infrastructure as enabler of innovative business models has to support these innovations by providing agile methods to quickly adapt to new use-cases. This underlines the need to manage the digitized environment systematically in order to foster efficiency. IT Service Management (ITSM) as a discipline evolved and now provides the framework to orchestrate the complexity in Information Technology. The activities, processes, and capabilities to maintain the portfolio are served by individuals, who interact with each other. There is an emphasized need for identifying, acquiring, organizing, storing, retrieving, and analyzing data related to human interaction processes to support finally the business processes. This paper proposes a conceptual data model to capture information about human interactions during support ticket administration (DMISTA). The presented model-structure and -requirements allow for efficient selection of appropriate data for various data science use-cases to understand and optimize business processes. The DMISTA supports different types of relationships (based on causality, joint cases, and joint activities) to enable efficient processing of specific analysis methods. The applicability of the model is shown based on a typical use-case.

1 INTRODUCTION

IT operations is nowadays a vital function in the business enterprises. Frequent changes in provided services are often part of the corporate strategies since constant re-invention and adaption is crucial to develop a competitive position in the global markets. The resulting shorter product lifecycles requires to constantly transform the organizations capabilities. Moreover, the actual global pandemic accelerated the transformation in digitalization, which leads to a paradigm shift in the products we assemble, the services we offer, and the way we collaborate. IT Service Management (ITSM) as a discipline provides the underlying framework to orchestrate (manage) the essential implementations in Information Technology. This is mainly done by handling the IT operations through considering standardized procedures and processes - mapped in digitized process landscapes. Basically, this field has much priority for research in optimization since IT operations accounts 70% - 90% of total cost of IT ownership (Fleming, 2005).

Processes are operated by individuals (the human actors in the network) who exchange and interact with each other. These interactions form the glue between the processes and can be considered as networks of interactions. One individual interacts with another individual and thus ensures that requirements are routed through the organization properly and implemented accordingly. In ITSM, this communication is mainly captured by using standardized and documented statements (support tickets), which are processed through supporting workflow management systems (ticket system). The rising complexity of the underlying service structure of most organizations results in a mass amount of ticket data which is mostly in business operations still underutilized. Applying intelligent approaches on the ticket administration activities has potential to discover valuable knowledge about the involved individuals and to foster efficiency by analyzing the interactions between them. Therefore, as a first step, a conceptual data model has to be developed to unify the description of the ticket structure and to enable further analytics use-cases, which aim on analyzing behavior and characteristics patterns of

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individuals. Based on this aim, the following research questions may be asked: *What are the requirements to model interaction-based data?*, and subsequently: *How could a conceptional ticket data model for interactions look like?*

This paper proposes a conceptual data model to capture information about human interactions during support ticket administration (DMISTA). The definition of interaction relies on the relations between entities in the data model. The DMISTA supports different types of relationships (based on causality, joint cases, and joint activities) to enable efficient processing of specific analysis methods.

In the following section, related work will be briefly discussed to classify the work into the research context. Subsequently, a use-case is introduced, motivating the necessity of the DMISTA. The requirements, structure and the model itself is introduced in Section 4. The paper concludes with a discussion of security and privacy demands and the outlook for further research.

2 RELATED WORK

The related work of data modeling in the relevant area can be structured in two main parts, respectively: (1) "What data models have been proposed in the area of ITSM and for which use-cases?"; and (2) "Aiming on deriving human interactions, what data modeling concepts have been proposed?".

Considering the first question, it can be concluded that much research in ITSM has been carried out to provide data models for implementing *text mining methods* (which aim finally on optimizations in ticket administration), such as (Asres et al., 2021) (Ferland et al., 2020) (Molino et al., 2018). A large number of these approaches rely on features that arise from ticket summary, description, and resolution text, supplemented partially by additional meta information. Accordingly, the underlying data models which were described aim on the tickets itself, not on the interactions between the individuals. Thus, to answer the second question, we have to consider adjacent areas. An example for a developed data model, based on general ticket management is described in the work from (Shao et al., 2008). The authors proposed an approach for a ticket routing recommendation engine (EasyTicket) that mines the steps of ticket transfers from one group to another. However, this approach aims on probabilistic workflow mining (instead of human interactions), which opens corresponding research questions. (Zisiadis et al., 2011) created the network trouble ticket data model (NTTDM) to provide the basis for storing as much as possible ticket data from multiple sources in a grid. The aim is to simplify the exchange of information between different operation centers to enable efficient cooperation. Since each of the sources operates its own ticket system, the definitions of entities and attributes in NTTDM are generic and maps to the formal definitions in ITSM to achieve a normalization. The outcome helps to verify the used metrics for our data model, although it aims on a different use-case.

Best results related to *data models that aims on human interactions around information systems* can be found in the area of process mining (e.g., based on event logs) and digital communication (e.g., e-mail exchange considered as communication logs). One of the first approaches to discover networks of individuals in log data was proposed by (Van der Aalst et al., 2005). The suggested metrics to define relationships can be used as inspiration to be mapped on ITSM. Further research in logfile- and communication mining deliver structures for data modeling in (1) *organizational development*, e.g., (Laclavik et al., 2011), which describes implicitly the requirements of a data model for organizational modeling (entities, attributes, and relationships) in e-mail communication; (2) *social networks*, e.g., (Ferreira & Alves, 2012), which proposes useful relationship metrics, such as "handover of work" and "working together" as identifier of relationships between individuals; and (3) *sociological and psychological areas*, e.g., an approach by (Agarwal et al., 2012) and (Gilbert, 2012) to model relationship metrics based on hierarchies.

3 MOTIVATION

A conceptual data model must be able to capture the requirements of different use-cases and should not be limited to a specific ticket system. Therefore, the conceptual schema represents the *core characteristics* of interest, thus can be easily extended to cover the use-cases (e.g., by adding additional attributes). Furthermore, it should support different types of relationships, which ultimately opens opportunities for research in interdisciplinary sciences such as data mining, business process management, or pedagogics. It enables the application of analytical data science methods on - in this case - the representation of interactions. The possible questions extend over the following five areas:

(1) Most of the research in ITSM aims on *improving efficiency* in ticket administration procedures. Im-

proved ways of interaction by the individuals involved leads to increased efficiency in processing tickets.

(2) The interaction between individuals provides information of *organizational development*. Aspects of asked questions in this area can relate to work assignments, work organization, skills and capabilities of individuals, control of the quality and quantity of the services provided, or the organizational structure.

(3) *Communicating Systems* are processing information and enable exchange between individuals via interactions. Possible research questions can relate to the information flow (e.g., unidirectional or bidirectional between individuals) and information processing (e.g., acquisition, storage, processing and output of information).

(4) *Statistical Analysis* of communication and interactions can help to identify dependent effects and characteristics.

(5) Human interactions are often linked to *sociological, psychological, and pedagogical* questions, which aim generally on interrelationships between acting partners. Possible questions in the area of ITSM could relate to hierarchies, roles, empathy, identities, language behavior, or the cooperation between all parties involved.

The research community around ITSM focusses mainly on questions which aim on (1) improving ticket administration efficiency. The degree of maturity of the processing has directly impact on the quality and continuity, which will be served as value to the customer. In the following, the activities of handling and processing tickets are also referred as *ticket administration*. (Kang et al., 2010) summarized following main issues, concerning ticket administration in IT operations:

Manual processing steps, i.e., activities such as gathering required additional information, analyzing characteristics within the provided data or workload that is associated with solving a ticket (ticket administration). These steps might consist of several interactions with the ticket system and are done mainly manually and individually. This is a labor-intensive work, therefore error-prone and time-consuming, that needs to be minimized to meet budget requirements. Subsequently, tickets are not being *processed consistently*. The different hierarchies in service management are based on a different depth of knowledge. Result is that the quality of resolution is dependent on the actors and may be not reproducible.

According to this description, a specific use-case would be the *ticket dispatching* step. In an IT service environment, the precise and timely dispatch of a ticket to the responsible resolution group is one of the crucial first step in the whole ticket administration procedure. The complexity of support structures in such environments results in challenging routing decisions which have to be made by individuals in the first level of the support structure. Incorrect dispatching decisions have impact on resolution times, therefore on financials and customer satisfaction.

With the DMISTA, we are able to develop optimization models to identify important individuals to route tickets directly to the expert. This leads to improvements in time-efficiency (optimized ticket routing) and gives a view on critical team members (identifying interesting influential members). Furthermore, the development of recommendation-engines focused on individuals and relations between them is conceivable. For example, the processing partner in between of the ticket issuer and resolver could play a crucial role in the whole support process as an individual with strong connectedness.

The described use-case highlights the benefits and necessity of the DMISTA from different angles. Accordingly, the data model must fulfil functional and non-functional requirements, which may differ while applying different use-cases. The *functional requirements* for modeling a database are given by the use-case, which provides the properties for the implementation. This is done by the definition and specifications of the core entities in an information system, required core attributes, and relationship types.

Non-functional requirements, on the other hand, indicate how qualitatively efficient the system should be. The international standard ISO/IEC 25010 (System and software quality models) defines (among others) performance efficiency, reliability, and maintainability of such non-functional requirements (International Organization for Standardization, 2011). A suitable architecture for a target DBMS should be selected that also considers the non-functional requirements.

Therefore, the DMISTA (1) must be based on *common standards* (ITSM) to be used generically and independent from a single ticket system; (2) must be able to store the *required core entities* to enable analytics on relations between individuals in the network; (3) must be able to store the *relevant core attributes* as identifier of the entities; (4) must be able to store and represent the *relevant relationships* on different levels to model human interactions; (5) must efficiently support the *processing of complex queries between relationships* of different entities.

4 THE DATA MODEL

4.1 Structure and Requirements

Derived from the use-case presented in Section 3, the DMISTA should not be limited to a specific service management system in an organization but contain specifications as generic as possible without accepting redundancy or losing characteristic. Thus, the DMISTA contains central core description of entities, attributes, and relations based on standards in ITSM. A historical ticket data log is suitable to deliver the data to fulfil the requirements. Entities are objects which can be distinctly identified and refers to the logical representation of data. For data modeling of interactions of individuals in a network its crucial to identify strong entities as anchor, for which their existence does not depend on any other entity. The characteristics of these entities are given by the attributes which are in context of the entity. The connection between two or more entities is called relationship. The key to the successful subsequent analysis of the interactions is the representation of the relationships between the individuals.

Requirements for data volumes and query times raise the question of a selection of the appropriate architecture for the logical and physical implementation. Considering the underlying data, different aspects need to be discussed to select the required database-model. As mentioned before, the ability to efficiently represent and process complex relationships is crucial. Relational databases (RDBs) are designed to managed tables and forms, which can be use-cases to aggregate highly structured data. Basically, relationships can be mapped in those, however, the amount of relations required to store highly networked information is very high and query processing leads often to complex sequences of data base operations (e.g., for depth search purposes). Relationships in RDB schemas do not directly reveal the semantics needed for ITSM analysis. Thus, this implicit information must be reconstructed in queries by using joins. To solve this problem a database that was explicitly designed to represent sequences of relationships, a graph database, could be used (Paul et al., 2019). The main advantage of employing graph databases is the explicit support to store and navigate relationships in a graph (G). Vertices (V) are utilized to store entities, while edges (E) describe directed, semantically connections between objects, with properties: $G = (V,E)$. Since the relations are not computed at query time but stored directly in the database, crossing the joins or relationships is efficient. Provided that the research in interactions in support ticket data is an application that involves a large number of relationships between the data, the graph databases are suitable in terms of performance. This has also been concluded in research, such as (Khan et al., 2019) (Rodriguez Reyes, 2021) (Stanescu, 2021) (Vicknair et al., 2010), where relational databases are compared against graph databases. According to the authors, typical projects for graph databases are storage and analysis of connections and relationships, mapping of complex relationships in collaborative systems, optimization of routing in networks, etc. - in general: connection-, highly networked-, or route problems. Investigations in interactions in ticket workflow management systems can be interpreted as an example of data in a collaborative system, where users interact with each other to achieve a solution for a specific request (described in a ticket).

4.2 Entities and Attributes

The entities to identify are those who are relevant to describe interactions in support tickets. The DMISTA contains the core primary- and associated entities in the structured and unstructured data of the ticket history logs. *Primary entities* describe the strong and associative entities, which consists of the main objects to research in and can be identified with Primary Key relations (see Table 1). *Associated entities* (weak entities) in this context consists of the artifacts which are generated while interacting in support tickets and refer with Foreign Key relations to the primary entities (see Table 2).

Table 1: Core primary entities in the DMISTA.

Individual	
Attribute	**Description**
UserID	Unique identification label for individuals.
E-Mail	E-Mail address of an individual.
Name	Name of an individual.
Ticket	
Attribute	**Description**
ID	Unique identification number for tickets.
CreationTimestamp	Date and time of creation of the specific dataset.
ClosureTimestamp	Date and time of closure of the specific dataset.
DescriptionText	Description of the ticket as free text.
SolutionText	Solution of the ticket as free text.

Major primary entity is the individual (the human actor) in the ticket network. He is involved in the ticket administration procedure, therefore of special interest for studies related to interactions. Usually, ticket workflow management systems consist of users (the individuals), who hold specific identifier and attributes (user-ids, clear names, e-mail addresses, etc.) to enable support ability. Furthermore, a ticket (second primary entity) can be identified by a unique id and consists of creation date, closure date, description text (short and long description) and solution text.

Additional attributes can be added to both, if required by the analytical use-case (such as priority (ticket), status (ticket), type (ticket), company (individual), department (individual), or telephone number (individual)).

Table 2: Core associated entities in the DMISTA.

ActivityLogEntry	
Attribute	**Description**
Timestamp	Date and time of activity.
IndividualUserID	Identification label for individual which act as author.
TicketID	Unique identification number for referenced ticket.
ActivityDescriptionText	Description of the activity performed by the individual as free text.
Topic	
Attribute	**Description**
TicketID	Unique identification number for referenced ticket.
TopicName	Content of activities categorized to describe the topic of the ticket.
ActivityCategory	
Attribute	**Description**
IndividualUserID	Identification label for individual which act as author.
ActivityCategoryName	Activity summarized in a category.

Associated entities are derived from activities - while the activity log entries reflect the actual descriptions of the activities, it is possible to derive further categorial entities from them, e.g., to describe relationships. An activity log entry contains Foreign Keys as set of attributes in a child table, since they refer to tickets and individuals as the primary entities.

4.3 Relations

Key is to define the types of relations between individuals or group of individuals, which can be derived from the ticket log data. (Van der Aalst et al., 2005) proposed different metrics to describe relations in the area of process mining in log data: (1) Relation metric based on *causality*; (2) Relation metric based on *joint cases*; (3) Relation metric based on *joint activities*; and (4) Relation metric based *special event type* (derived from the data that the researchers employed, therefore not applicable in ITSM).

In the following, the first three proposed metrics will be used as inspiration to develop own description of metrics, that fit to the ticket administration procedures in ITSM.

4.3.1 Relations based on Causality

Causality is the relation between cause and effect, based on a sequence of events that are related to each other. This principle can be found in the ticket lifecycle by defining corresponding associations. A simple relation, which can be used as a good starting point is the contribution of different individuals in one specific ticket. The assumption is, that all actors, who are involved in resolving that ticket ("handover of work"), are related to each other (see ERD in Figure 1). This principle can be extended to all involved individuals, even if they are just mentioned in the activity description (e.g., e-mail chains as "working together"-metric).

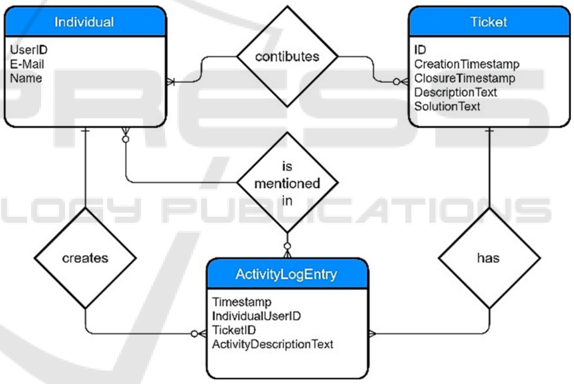

Figure 1: ERD: Relations based on causality.

The frequency of interaction within a timeframe between those individuals define the intensity of relationship and can be used to assess the role of an actor in the network. Furthermore, the timestamp of the events in the ticket history can be used to create causal relations by combining the information of different tickets. Related questions can be answered, such as: „How are individuals interconnected?"; „Who is performing best (in resolving tickets)?"; and „Who is centralizing the communication as focal point („men in the middle")?".

4.3.2 Relations based on Joint Cases

To derive relations based on joint cases, it is necessary to define a case. Related to ticket management, a case is a *topic* that is defined by the ticket itself (what the ticket is about). Therefore, an approach is to classify the unstructured data in the ticket description text to determine its topic or topic category (see ERD in Figure 2). Thus, it reveals how often an individual works on one specific case. Once the resulting datasets of different individuals are similar to each other, it is likely that the individuals are related, since they are working on joint cases. This can be achieved even without considering any kind of causal dependency. Text mining methods provide different approaches to achieve the topic classification or clustering. The more often two individuals work on the same case, the stronger the relation. This could be developed further, e.g., by considering the kind of activities performed for the specific case.

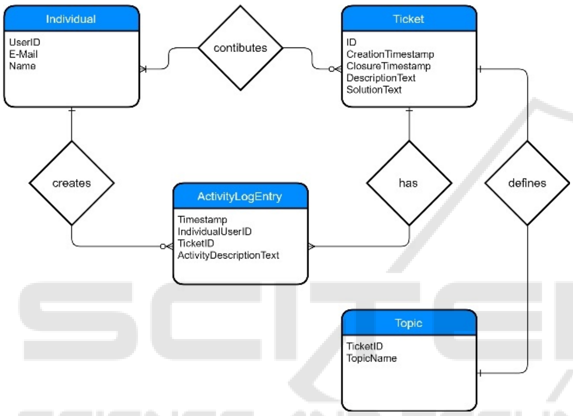

Figure 2: ERD: Relations based on joint cases.

Identifying the groups of individuals working on same or similar problems could help, e.g., to address optimizations in routing challenges by detecting the right people for the requested domain. Furthermore, the synergies within the different teams who are working on same topics can be promoted, once the collaboration of experts gets fostered (e.g., by providing a shared knowledge base, creating space to share experiences, or implementing coordinated procedures). Subsequently, organizational structures can be improved in accordance with the findings of how the teams are distributed.

4.3.3 Relations based on Joint Activities

The definition of joint activities relates to individuals, who are performing similar or same activities (instead of completely different activities). Once we find individuals executing activities from the same category (activity profile), it is possible to create a relationship. The basic assumption is: The more often two individuals perform same or similar activities, the stronger the relationship - ignoring the specific topics they are working on. The correlation between the individuals can be calculated, e.g., by measuring the distance of the activity-profiles. Mapped on ticket management, these profiles can be derived by processing the content of activity log entries through suitable classification or clustering algorithms.

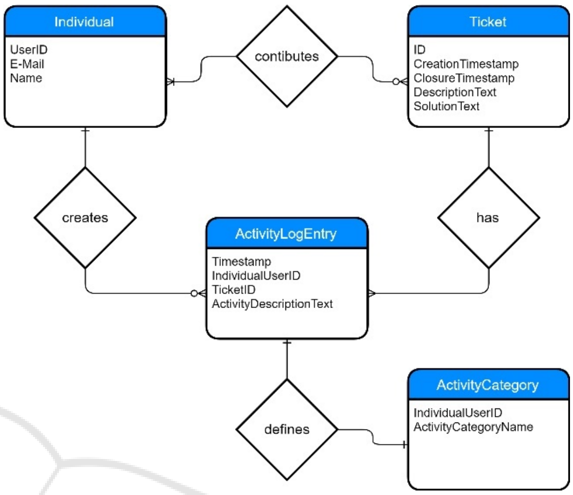

Figure 3: ERD: Relations based on joint activities.

Relations based on joint activities provide the answer to the question of „Who is doing what and which activity profiles can be created from this insights?“. Dependent on the results, this enables to identify the individuals, who are involved in important activities, such as resolving the tickets. Applied on a specific part of organization, it helps to foster efficiency (e.g., to improve routing decisions), but also to change procedures if bottlenecks are identified (e.g., increased amount of unproductive activities). Activity profiles provide information about the value a specific group delivers. Combined with further metrics, variations can be researched to extend the insights.

4.4 Implementation

We developed a prototype which implements the DMISTA to validate the data models' ability to store the required ticket data. Two raw datasets are available for research purposes: Ticket *corpus 1* sourced from entertainment-branch (112,452 ticket history datasets within three years) and ticket *corpus 2* from industrial-branch (15,300 ticket history datasets within one year). On average, one ticket history dataset consists of 6,5 entries. Both originate from different ticket tools and branches, which allows the validation of the effectiveness of the achieved research results. All datasets were derived from primary sources and were captured from large-scale corporate background. The datasets were initially classified into subsets to investigate in the organizational properties of a predefined technical area (example group).

In the following, one example group derived from corpus 2 will be described to illustrate the results. Based on 4,935 history entries from approximately 3 months, we were able to successfully store 750 ticket entities and 492 individual entities. Relationships were derived accordingly. Based on the data model, we implemented different analytical use-cases. One of them was to identify central actors in the interconnectedness set of relations which are structurally strong integrated, using *degree centrality* (refers best to a question of category (4): Statistical analysis - see description in Section 3). Centrality measures are part of network science and uses mathematical methods to systematically analyze graph structures. For the group selected, we were able to identify the group characteristics, especially the set of major contributors (possible key players). Four individuals show significant higher numbers of connections to its neighbors, compared to the others. We conducted a separate verification-step with domain experts, who validated the results. They confirmed the central role of those individuals in the ticket administration procedure. We were able to identify the service responsible, two technical engineers with special knowledge, and one central individual who routes the tickets.

The first results showed that the DMISTA works according to its requirements and is able to store the required ticket data. The modeling capabilities were cross validated based on datasets from two different areas. The next planned step is to provide a benchmark dataset in order to be able to deepen the research in ticket interactions and to provide traceability.

5 SECURITY AND PRIVACY CONSIDERATIONS

The paper defines the DMISTA to enable research in the defined area. The model itself does not raise any type of security and privacy concerns. However, it is crucial to consider appropriate data and security carefulness while handling the primary sources. These questions arise from different perspectives, e.g., the storage of data (access management, encryption, etc.), the publication of results (public, internal, etc.), or the usage in applications. Individuals can increasingly collect datasets about communication behavior, identifier and company-related aspects using common tools and technologies. The data collected within the ticket corpus can be both, personal (e.g., the activity profiles of individuals) and business sensitive (e.g., information about system vulnerabilities). This form of data invokes challenges and value judgments while applying information sciences, considering the type of user participation, rights and agency of data collectors, and what type of information will be processed.

To take these aspects into account, the appropriate measures have to be initiated. Considering publication purposes for research, the *"Guide on Good Data Protection Practice in Research"* (European University Institute, 2019) proposes a series of activities: As a precondition, a data preprocessing step needs to be implemented to ensure anonymization. Features that are suitable to identify directly or indirectly personal or corporate data will be replaced by parameters using randomization, generalization and pseudonymization techniques. This approach is commonly applied in network analysis research. Depending on the application to be developed, it is necessary to consider further measures to effectively protect personal privacy and business sensitive information.

6 CONCLUSIONS

The maintenance of complex system environments in ITSM includes a huge amount of quantitative and qualitative aspects, which have to be detected, logically organized, retrieved, and stored to be finally analyzed in research. The DMISTA contributes to researchers and organizations that collect, manage, analyze, and interpret ticket information in a proper and consistent way. Studying the interactions in the ticket data is an open question in research, which have to be based on relevant and accurate statistical data that rely on properly designed, frequently updated, and maintained databases.

The DMISTA (1) aims to enable research in human interactions use-cases by modeling relationships on different levels; (2) provides a common format that allows researcher to store, exchange, manage, and analyze support tickets; (3) identifies relevant core entities and attributes; (4) is effective, as it captures the core characteristics of individual's activities during ticket administration procedures. It is also dynamic to future demand, as it allows to be enriched by additional components; (5) can address key questions from research area in ITSM, including efficiency-, organizational-, communication-, statistical-, and sociological, psychological, pedagogical-related questions.

It is planned to provide a benchmark dataset to be able to discuss further research results in the community. Moreover, our DMISTA opens interesting questions in ITSM to be analyzed in our future work.

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