Case Model for the RoboInnoCase Recommender System for Cases of Digital Business Transformation: Structuring Information for a Case of Digital Change

Hans-Friedrich Witschel, Marco Peter, Laura Seiler, Soyhan Parlar and Stella Gatziu Grivas
FHNW University of Applied Sciences and Arts Northwestern Switzerland, Switzerland

Keywords: Case Model, Recommender Systems, Decision Support Systems, Digital Transformation.

Abstract: In this work, we develop a case model to structure cases of past digital transformations which act as input data for a recommender system. The purpose of that recommender is to act as an inspiration and support for new cases of digital transformation. To define the case model, case analyses, where 40 cases of past digital transformations are analysed and coded to determine relevant attributes and values, literature research and the particularities of the case for digital change, are used as a basis. The case model is evaluated by means of an experiment where two different scenarios are fed into a prototypical case-based recommender system and then matched, based on an entropically derived weighting system, with the case base that contains cases structured according to the case model. The results not only suggest that the case model's functionality can be guaranteed, but that a good quality of the given recommendations is achieved by applying a case-based recommender system using the proposed case model.

1 INTRODUCTION

Digitalisation is changing everything around us, and it seems as though it is here to stay. With good reason: companies that have decided to undertake a transformation of their business model have found themselves to be more competitive in today's market (PwC Schweiz, 2016). Investments in digitalisation activities correlate to the perceived increase in competitiveness. However, the trend affects all sizes of organisations in all industries. This, unfortunately, is where this development, with seemingly endless possibilities, has a catch. As the survey "Digital Switzerland" states, "a majority of 87% of Swiss small and medium-sized enterprises (SMEs) can be classified as so-called digital dinosaurs" (HWZ and localsearch, 2018). Missing resources tend to be the number one challenge SMEs must deal with during a digital transformation. Another finding reveals a lack of know-how about the impact of digital technologies on their business, which makes it difficult to exploit the number of digital opportunities in daily business (HWZ and localsearch, 2018). This is especially important for SMEs which are under the pressure of competitors. To support SMEs towards a successful and sustainable digital transformation, the ABILI Methodology (Peter et al., 2018) offers a systematic and transparent transformation process, amongst others focusing on the inspiration phase by identifying so-called cases for digital change. In this inspiration phase, SMEs understand their current internal situation and their core capabilities as well as external influencers (like new competitors, new customer demands or new technologies) and get ideas about possible transformation paths such as innovation, process automation or organisational changes. The analysis is supported by two web-based tools, the Digital Backpack Assessment and the Panoramic Lens (Gatziu et al., 2018). This is the starting point for the further in-depth analysis, including the definition of strategic goals for the digital transformation. For this analysis, the ABILI Methodology offers the Transformation Compass (Graf et al., 2018).

The lack of know-how mentioned above is manifested especially in this inspiration phase. To overcome this, we propose an intelligent recommender system, the RoboInnoCase, which, depending on the current internal situation of the companies and taking into account the external influencers, makes suggestions for cases of digital changes. Thus, the company receives an array of recommendations that are customised to its needs. Experiences of past consulting cases are also collected and saved in a case base to be accessed by the recommender system.

Witschel, H., Peter, M., Seiler, L., Parlar, S. and Grivas, S.
Case Model for the RoboInnoCase Recommender System for Cases of Digital Business Transformation: Structuring Information for a Case of Digital Change.
DOI: 10.5220/0008064900620073
In *Proceedings of the 11th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2019)*, pages 62-73
ISBN: 978-989-758-382-7

In this paper, we discuss a case model to structure the cases of past digital transformations which act as input data for the RoboInnoCase recommender system. The tailor-made set of recommendations, which are then provided by the recommender system, is to be understood as the output data, or the case for digital change.

The paper is organised as follows: related work is discussed in Section 2 and our research methodology in Section 3. Section 4 describes our proposed solution for a case model for cases of digital business transformation. The evaluation of the case model is presented in Section 5 and discussed in a concluding manner in Section 6.

2 RELATED WORK

2.1 The Core of Digital Business Transformation

Digital transformation is rather unique to every business. However, there are a few concepts in literature representing similar core parts of every company's digital transformation. Studies have shown that managers generally transform four key areas of business as part of a digital transformation within a company (Westerman et al., 2011):

- Customer Centricity
- Operational Excellence
- Business Model
- Organizational Excellence

The Transformation Compass of the ABILI Methodology is built around these four transformation building blocks (Graf et al., 2018). These blocks also give the structure of the Digital Backpack Assessment, which is used for the analysis of the internal situation of the company and is a starting point for the definition of the case structure for the RoboInnoCase.

The first building block, customer centricity, shows how a company empowers its customer, how it is attracting the customer, how the company is interacting with the customer and enhances the customer's respective experiences. Operational excellence includes operational processes, strategy, and corporate management as well as the dataflow within an organisation. It mostly aims to increase efficiency. Another key area for SMEs is to recognize enablers which lead to market growth and innovation. Those aspects are included in the third building block called business model. The last building block, organizational excellence, is linked to the cultural aspects and the way people are managed and led in a company such that the organisation learns and improves its capabilities.

In Section 4, we will use the key areas to structure recommendations and derive them from corresponding aspects of a company's initial situation – such as its current customer segments or core business processes.

2.2 Case for Change

At the beginning of every systematically created innovation is a formulated "Case for Change" (Dobni et al., 2015). The case for change is defined as follows: "a case for something" = there is an existent necessity and change = transformation (Dr. Kraus and Partner, n.d.). In short, the case for change describes the reasons for a change. However, the purpose of a case for change is not only to explain the particular reasons for a change, it should also (The Change Source, 2013):

- Highlight desired outcomes and expected benefits
- Demonstrate leadership support

Through this, it is meant to:

- Minimise the resistance to change
- Gain support from internal as well as external stakeholders that are impacted by said change

To create a case for change, there are some guidelines that have been proposed in business communities (Jones et al., 2004). As a first step, the organisation's current internal and external situation should be analysed and used to deduce the need for a change. Secondly, it is important to point out if and how the company, its management as well as its staff are able to cope with the change (Jones et al., 2004). Additionally, one should also articulate what exactly will change and who will be impacted by these changes (Jacoby, 2012). Thirdly, a roadmap should be developed, showing how the proposed change will be implemented, how the management should behave and how it should make decisions concerning this innovation. Further, one should highlight the expected benefits resulting from these changes as well as the consequences of delaying the changes. At last, it is important to inform the various stakeholders "about what is expected of them" to point out that everyone is part of implementing the changes successfully (Jacoby, 2012). As this paper is concerned with finding a way to provide suitable change recommendations for a company, we focus on what will or could change and what outcomes or benefits may be realised.

2.3 The Recommender System in a Nutshell

Most current recommender systems (RS) are built to provide recommendations that help individuals to decide which products, goods or services to buy or use, usually based on their personal preference. Generating recommendations for personal preferences is not the only purpose of a RS (Witschel and Martin, 2018a). There are also recommenders which create suggestions for business decisions, driven by business requirements rather than individual preferences (Tiihonen and Felfernig, 2010; Witschel and Martin, 2018b). The starting point for such business recommenders is different from end-user recommenders since business recommenders are often invoked just once (or at least very rarely) by a company and thus the system cannot collect information about the user from repeated interaction (Felfernig and Burke, 2008). This means that such systems usually need to acquire their inputs (the business requirements) via some kind of questionnaire – in our case, much of the input is acquired using the two online assessment forms mentioned in Section 1. Such a process resembles the process of business consultancy – and, as the consultancy industry itself undergoes a digital transformation (Nissen and Seifert, 2017) – may partially replace the humans in that process.

In a nutshell, RS are useful tools that can support not only individuals but also businesses in decision-making. The RS merges methods from information retrieval and filtering, user modeling, machine learning, and human-computer interaction (Bridge et al., 2005). For the development of case-based RS or content-based RS, knowledge about case-based reasoning, which is explained in Section 2.3, is essential (Bridge et al., 2005).

2.3.1 Recommendation Techniques

According to Bridge et al. (2005), case-based approaches to recommendation have their place as special forms of both knowledge-based (Aggarwal, 2016) and content-based (Pazzani and Billsus, 2007) recommendation. As states by Ricci et al. (2011), a knowledge-based RS recommends items based on specific knowledge about how an item feature meets a user's needs. A case-based RS assesses a user's need (problem description) for the recommendations (problem solutions) through a similarity function. In this case, a similarity assessment can be understood as the benefit of the recommendation for the user.

As explained above, typical situations in business consultancy may allow the system to acquire information about a (current) user need, but usually imply that no rich history of the current user is available – a common cold-start problem (Lika et al., 2014) in collaborative filtering recommenders (Schafer et al., 2007) that are commonly used for preference-based recommendations, e.g. in e-commerce. This makes content-based recommenders a better choice. Since consultancy draws a lot on the re-use of experience (Gable, 2003), case-based techniques are a perfect match. The theory behind case-based RS is explained in the following section (Ricci et al., 2011).

2.4 Case-based Reasoning

Case-based reasoning (CBR) is a theory for solving problems with the help of remembering a similar situation that has happened in the past and subsequently reusing this knowledge and information of that particular situation (Aamodt and Plaza, 1994). Regarded as “a subfield of machine learning”, CBR facilitates sustained learning by retaining the experience of successfully solving a problem for future, similar problem-solving. Thus, it continuously updates the case base, the collection of cases, following each problem that has been solved. The steps or process necessary to conduct problem-solving is also called the CBR working cycle (Aamodt and Plaza, 1994). Kolodner (1992) identifies the following process steps when applying CBR: case retrieval, case adaptation, solution evaluation, and case storage. Applications of CBR range from medicine (Choudhury and Begum, 2016) over law (Rissland et al., 2005) to business process re-design (Mansar et al., 2003).

2.4.1 Case Representation

A case contains pieces of knowledge that represent a particular experience. In general, cases comprise a (Kolodner, 1991a):

- **Problem Description:** a description of the situation at the occurrence of the case
- **Problem Solution:** the solution that has been applied to the problem

As this definition shows, the notions of problem and solution can be understood in a wide sense: a “problem” might simply refer to an initial situation – such as the situation of a company – where no immediate pain is felt. However, in what Kolodner (1991b) calls interpretive CBR, one “evaluates new situations in the context of old solutions”. For our goal of inspiring companies on how to transform digitally, this means that we evaluate their situation by looking at the contexts of other companies and what they did to maintain their competitiveness in the digital age.

Case representation in CBR applies knowledge representations to describe the experiences contained in cases for the purpose of reasoning (Bergmann et al., 2005). In terms of representation, there is a distinction between three CBR types that should be made: "structural, textual, and conversational" (Bergmann et al., 2009). Here, the focus is put on structured cases as we want to establish a common case structure with controlled vocabulary to overcome problems of e.g. synonyms that are inherent to e.g. textual representations. In structural CBR, cases are represented with attributes and corresponding values (Bergmann and Schaaf, 2003). It is especially useful in instances where further knowledge, besides cases, have to be used to generate satisfying results (Bergmann and Schaaf, 2003). Below, the representation formalisms that were observed most in literature are described in more detail:

A. Frame-based representation

In frame-based representations, frames are used to combine the necessary knowledge concerning an object or concept (El-Sappagh and Elmogy, 2015). A frame organises the knowledge in forms of slots defining the characteristics and attributes of the object. This means, in terms of CBR, that a case can be represented by a frame and every case feature is characterised by a frame slot. Slots can contain primitive values as well as pointers linking to another frame. The frames, or cases, may have semantic relationships as they can have features (slots or attributes) whose value is a pointer to a different frame. Additionally, the "cases connected by IS_A and PART_OF relationships" can be hierarchically structured as inheritance is one of the essential features of the frame. This hierarchy improves the retrieval, indexing as well as the adaptation of the cases (El-Sappagh and Elmogy, 2015).

B. Object-oriented representation

In situations where the case data structure is more complex or incoherent, object-oriented representation may be more suitable (Bergmann et al., 2005; El-Sappagh and Elmogy, 2015). The expressiveness is similar to the frame representations, also making use of IS_A and PART_OF relationships and the inheritance principle. A collection of objects, that are each described by various attribute-value pairs, represents a case (Bergmann et al., 2005). The object class describes the object's structure (El-Sappagh and Elmogy, 2015). One can distinguish between so-called simple attributes, such as integers, and relational attributes (Bergmann and Schaaf, 2003). Relational attributes symbolise binary relations, such as part-of relationships, between the objects defining the relational attributes and the objects to which they refer. Thus, it is possible to relate objects to other objects of some arbitrary classes, enabling the appropriate representation of cases with various structures. Most modern CBR systems nowadays use object-oriented representation (Bergmann and Schaaf, 2003).

C. Hierarchical case representation

The before-discussed methods focus on representing a case at one level of abstraction (Bergmann et al., 2005; El-Sappagh and Elmogy, 2015). It has, however, been shown that cases can also be represented by using a multitude of "representations at different levels of abstraction".

2.5 Contribution

To the best of our knowledge, CBR and CBR-based recommenders have not been applied to the problem of inspiring companies regarding their potential digital transformation. Since more and more companies are undergoing such change and are thus collecting experiences in this field, CBR seems a natural choice to support other companies in learning from these experiences. We make a first step toward such a CBR-based RS by developing an appropriate case structure for a "digitalisation case base". Since there are many success stories of digital transformations around (formulated in natural language), building up a case base will be a logical and feasible next step.

3 RESEARCH METHODOLOGY

The objective of elaborating and creating an appropriate case model for cases of digital business transformation, that are fed into the RS, have led to the decision to apply a design-oriented research approach in this research paper.

We follow the Design Science Research (DSR) process model proposed by Vaishnavi and Kuechler (2004), with its 5 phases *awareness of the problem*, *suggestion*, *development*, *evaluation*, and *conclusion*.

In the awareness phase, besides our literature research on digital transformation and CBR, we collected 40 cases of digital transformation, mostly through online research, but also using stories from our own and from acquaintances' work environment. To gather a relatively broad variety of cases, we selected cases from different industries, sizes, and age. These cases were then, in a further step, qualitatively analysed by coding, where we indexed and categorized the whole text in each case of a past digital transformation to create a framework of thematic ideas, to determine relevant attributes and values which were then part of the later elaboration of the case model. The results of these analyses were then used to build a first suggestion of a possible solution (suggestion phase of DSR). Therein, we used the knowledge about common approaches to case modelling in CBR (see Section 2.3.1), as well as about the key areas of digital transformation (Section 2.1) to structure the codes and determine their relationships.

In the evaluation phase, the suggested structure was evaluated by means of a qualitative test. For this, we built the case base with our 40 cases from the awareness phase, based on the defined case model, and the RS was enriched with information such as an industry taxonomy, to allow a better assessment of similarity between industries. Then, two test scenarios were defined which were fed into a simple case-based recommender that we implemented. To evaluate the recommender outcome in these scenarios, we first formulated assumptions and expectations regarding the results, which we then compared to the output of the RS. The results of the test run are discussed as to the case model's functionality and the recommendations' quality.

4 DEFINING THE CASE MODEL FOR THE RECOMMENDER SYSTEM ROBOINNOCASE

4.1 Categorisation of Parameters and Scope of Case Model

In the next subsections, we will discuss our suggested case structure from a conceptual perspective. It comprises 4 main areas: a characterisation of the company (in terms of industry, size, customer segments, etc.), of the challenges the company faced before the transformation, of the measures taken as part of that transformation and finally a characterisation of the outcome of applying these measures. In the following, we give the rationale and some details for each area.

4.1.1 The Transformed Company

To retrieve cases for inspiring a company's potential transformation, one needs to be able to describe the company's initial situation and its characteristics so that retrieved cases are as relevant as possible to that situation.

One of the parameters that plays a role in this is the size of the company. Size plays an important role regarding the feasibility of the transformation measures, as micro-businesses often have a lack of human as well as financial resources compared to middle-sized companies. Additionally, smaller companies tend to be less mature in terms of digitalisation due to the before-mentioned reasons.

On the other hand, the age of a company may not only be a further indicator of its overall digital maturity, but it may also point out challenges in the organisational culture to be overcome. As a change culture is one of the key elements of transforming successfully, and the age of a company can indicate some degree of change-adversity, it represents an important parameter in this case model.

Similarly, the industry of the company has a large influence since it determines many other key factors, such as core business processes or common customer segments. Furthermore, it can point out industry-specific trends and challenges that may impact digital transformation measures as well as present a last indicator of digital maturity as certain industries are more advanced than others.

In addition to these rather general information elements, it is essential to get a more in-depth view of the case company. For this, relevant building blocks of the business model canvas (Osterwalder et al., 2011) serve as a basis. In particular the building blocks that are concerned with the value (external view) of the business model are featured in the case model, such as the value proposition, the customer segments, the customer relationships, the channels, the key activities as well as the revenue streams. We place more emphasis on these elements of the business model canvas since they can more easily be researched by an outside party than the elements concerned with the efficiency (internal view) of the business.

4.1.2 The Challenge

To demonstrate the importance of the digital transformation for the organisation, the challenges faced are elaborated. While the variables identified in Section 4.1.1 were mostly based on findings from the literature, the aspects, relating to the drivers and the strategic goals, we refer to here were mostly taken from the analysis of our collected cases.

During our case analysis, we found that the reasons for a digital transformation can be generalised rather easily. Be it the increase in efficiency of processes, the change in customer expectations, necessity for cost savings or the need for a better differentiation to increase competitiveness. The reasons for the digital transformation are heavily interlinked with the measures taken by the company. Furthermore, the strategic goals of the company's transformation more clearly represent the overall objective of the taken measures.

4.1.3 The Transformation Measures

To make suitable recommendations, the measures taken in previous cases need to be understood. This means that such measures are part of the *solution* of a case. As mentioned in Section 4.1, the Transformation Compass suggests that there are four key areas of a business that are usually transformed, the so-called building blocks of digital transformation. To identify the characteristics of the taken measure it is important to know which of these four areas, organisational excellence, customer centricity, operational excellence or business model, it covers. These areas are then divided into further subcategories, corresponding to codes that we derived during case analysis in the awareness phase and allowing the identification of the measure's characteristics to get more specific. In the end, the specific measure that was chosen is described to give the company to be transformed a choice of possible solutions. In addition to the solution itself, of special interest to the company wanting to transform is the course of action that should be taken to execute the chosen measure. Thus, the case model considers various aspects of the possible course of action, such as the used development methodology and tools as well as the trends the measure was inspired by.

4.1.4 The Result

Lastly, the result of the taken measure is of major importance to the company wanting to transform. Primarily, it is essential to know whether the solution was a success or not. However, we strongly believe that unsuccessful solutions should not be ignored entirely, but that they should be analysed, to avoid pitfalls and to be able to optimise their measures to fit the needs or circumstances of the company wanting to transform. Unsuccessful cases should represent lessons learnt, not failures. The success of a solution is most easily determined by the achievement of the strategic goal set by the company. Further, certain improvements or optimisations (or problems) that have occurred as a result of the taken measure as well as the benefits or advantages of those improvements are highlighted. The drivers of the digital transformation may serve as a basis for representing the improvements as well as the advantages of the taken measure (e.g. improvement = increase in process efficiency, advantage = higher productivity or increased competitiveness).

4.2 The RoboInnoCase Case Model

4.2.1 Sets

In general, our proposed case representation is divided into a problem as well as a solution set. However, when considering the scope of the case model concerning cases of digital transformation, a model including two sets is insufficient. To give proper recommendations for specific transformation measures, a case must essentially contain not only the problem and solution sets, but all the information required to describe a case company in detail and the outcome of the chosen measure (see Section 4.1).

Thus, the case model for cases of digital transformation includes the following four sets: general information (G, see Section 4.1.1), problem description (P, see Section 4.1.2), solution (S, see Section 4.1.3) and outcome (O, see Section 4.1.4):

$$C = G \cup P \cup S \cup O \tag{1}$$

Moreover, the union of all cases defines the case base:

$$C_i = G_i \cup P_i \cup S_i \cup O_i \tag{2}$$

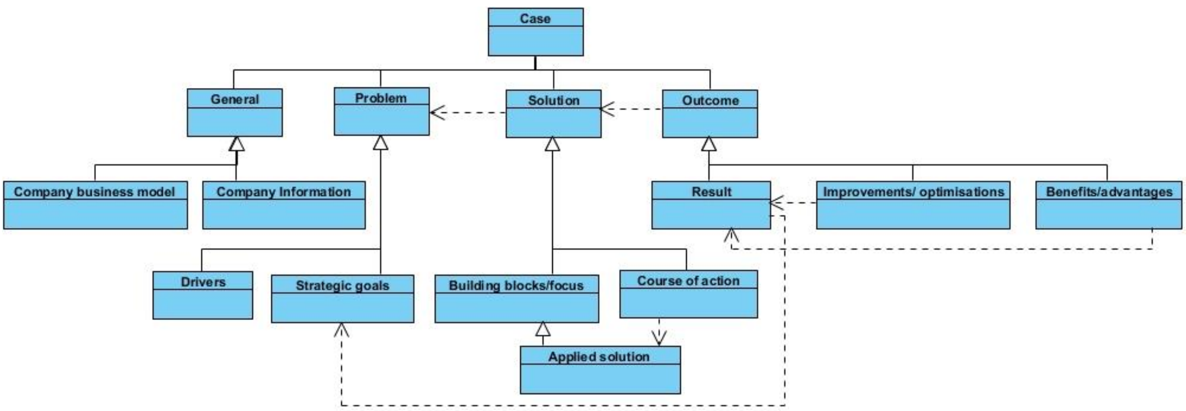

Figure 1: Case model for cases of digital business transformation.

Table 1: Attribute-value table for case model (1/2).

Company business model	Drivers	Strategic goals
Value proposition (e.g. Newness, Performance); Customer segments (e.g. Mass market, Niche market); Business relation (e.g. B2C, B2B); Customer relationships (e.g. personal assistance, self-service); Channels (e.g. own, partner); Revenue streams (e.g. asset sale, usage fee); Key activities (e.g. production, problem solving);	Increase in process efficiency; Changing customer expectations; Cost savings; Technical progress; Faster processes; Greater transparency within the company; More individualized customer offer; Exploitation of new market and sales channels; Added value for employees; New standards in the value chain; Others;	Increase competitiveness; Improve customer experience; Open up new market; Optimise processes; Develop in-house expertise; Optimise efficiency of employees; Solid market growth; Digitalized business model; Cost advantage compared to competitor; Others;
Company Information		
Industry (NACE classifications); Size (<10; <50; <250; >=250); Age (<5; >=5);		

Table 2: Attribute-value table for case model (2/2).

Building blocks/focus	Improvements/optimisations
Organisational excellence; Customer centricity; Operational excellence; Business model;	Stability; Competitiveness; Skilled employees; Customer acquisition; Establish in a new market; Company expansion; Improved information flow; Digitized processes; Reduce costs; Develop new digital units; Apply new digital trends; Successful market entry; Automatized processes; Others;
Applied solution	
Organisational excellence solution; Customer centricity solution; Operational excellence solution; Business model solution	
Course of action	Benefits/advantages
Development methodology, framework and model (e.g. Agile software development; Incremental); Development tools (e.g. Kanban; UX Design); Stakeholders involved (e.g. Employees; Customers); Analysis methods (e.g. Data analysis; Business analysis); Technological trends (e.g. Artificial Intelligence; Machine learning); Duration (e.g. < 6 months; < 12 months; < 18 months; > 18 months); Core activities (e.g. Processes; Requirements);	New digital business model; Customer satisfaction; New innovative product; Gain Knowledge; Agile units; Others;
	Result
	Success (yes/no)

4.2.2 Case Representation

To provide a more specialised representation than the four sets defined above, the knowledge collected throughout the research is appropriately categorised. Since the case data structure is rather complex and often inconsistent due to each case's individuality, an object-oriented representation was chosen. Additionally, because of the case data structure's complexity, the authors have chosen to apply a hierarchical case representation, allowing a case to be represented at numerous levels of detail. Thus, for the case model for cases of digital transformation, a hierarchical, object-oriented case model is created (Figure 1).

A case is represented by the "Case" object, which uses four objects on a lower level, corresponding to the before-defined sets "General", "Problem", "Solution" and "Outcome". The "General" object contains two lower level objects called "Company Information" and "Company Business Model" (table 1), representing the information needed from the case company. The "Problem" object consists of another two lower level objects, "Drivers" and "Strategic Goals" (table 1) which capture the past problem situation of the case company. The "Solution" object uses a lower level object called "Building Blocks/Focus", which uses a further lower level object, "Applied Solution" (table 2). In addition, "Solution" consists of another lower level object called "Course of action" (table 2), representing, amongst others, the tools and methods, such as agile software development or native development, used to implement the chosen solution. Lastly, the "Outcome" object makes use of three lower-level objects which are "Result", "Improvements" and "Benefits" (table 2), representing the outcome of the "Solution" object.

4.2.3 Relationships

As the case model shows, various relationships exist between the different objects. Firstly, there are certain important multiplicities that need to be explained. The case model can ever only represent one case. This case can consist of one "General" object, meaning a case can only involve one company. Further, a case contains one "Problem". If there is a company that deals with different problems, a case for every problem is generated since each new case is used as a query. Thus, the RS should return a suitable recommendation for every problem a company deals with. Every case consists of one "Solution" and one "Course of action". Lastly, only one "Outcome" can exist for a case, as a case may either be a success or not and has one set of improvements and benefits. Furthermore, there are various dependencies within the case model. For the "Solution" object, the "Course of action" is dependent on the "Applied solution" as it may impact attributes such as the development methodology and tools. Further, the "Outcome" is dependent on the "Solution" object since the "Applied solution" or the "Course of action" may have been an unsuitable choice for the problem at hand. Thus, the "Solution" object is dependent on the "Problem" object as well. When looking at the "Outcome" object in more detail, it is apparent that the "Improvements/Optimisation" and "Benefits/Advantages" objects are both dependent on the outcome. However, if the outcome was not a success, both the "Improvements/optimisation" and the "Benefits/advantages" objects can still be used to indicate which improvement or benefit could not be realised. This helps characterise the "failure" in more detail. Furthermore, to tell if an outcome was a success or not, it is most practical to check if the strategic goal that was set in the beginning has been (partly) achieved. Thus, the "Result" object is dependent on the "Strategic goals" object, which then, respectively, also influences the "Improvements/optimisation" and the "Benefits/advantages" objects.

4.2.4 Information Representation

When applying the object-oriented case representation method, a case consists of a collection of objects. As represented above, the case model for cases of digital transformation contains four higher-level objects that each consist of various lower-level objects. These objects are each described by various attribute-value pairs. To define each value-attribute pair, the following structure was applied:

- Name: describes the information entity
- Description: defines the meaning of the information entity
- Type: specifies the attribute type
- Value representation: describes how the value, corresponding to the attribute, is represented

Due to the fact that similar facts or situations can be expressed differently in natural language (Furnas et al., 1987), we have decided to define a set of controlled vocabulary for most attributes. Thus, the type "choice" is most frequently used, either with a choice of values or yes/no. For attributes where no controlled vocabulary could be defined, a "string" or "integer" value can be inserted. An attribute-value pair (A) of an information entity can be represented by a variable:

$$A= \{\text{name, type, value}\} \quad (3)$$

Where Name(A) = name, Type(A) = type, Value(A) = value.
Thus, a case (C_i) of digital transformation can be represented by a set of attribute-value pairs:

$$C_i = \{A_1^i, A_2^i, A_3^i, \dots, A_N^i\} \quad (4)$$

Where $A_j^i = j$th attribute-value pair in case i & N = number of attributes in a case.

All cases in the case base will have the same name as well as the type of an attribute-value pair, however, the value element may differ.

5 EVALUATION

5.1 Experimental Set-up

To evaluate the defined case model, we conducted an experiment with a prototypical case-based RS. The goal of the experiment is to evaluate the functionality of the case model and the quality of the output data of the RS. Quality in this context means that the recommendations accurately reflect the characteristics and the need (general and problem object) of the query. To build an experimental case base, the before-analysed cases were structured according to the case model defined in section 4.2. An exemplary row is shown below:

```
{attributes:NAME=example-case; INDUSTRY
business services, SIZE >=250, AGE >=5,
…}
```

The upper-case lettered strings represent the particular attributes, whereas the lower-case lettered strings are the respective values. Further, we configured the system by defining which attributes should be used as problem characterisations ($G \cup P$ as defined in Section 4.2.1) and which should be part of the system's output ($S \cup O$). The following attributes and their corresponding values should be returned:

- Building blocks
- Applied solution
- Course of action
- Benefits and improvements

5.2 Prototypical Case-based Recommender System

To receive meaningful results, we have developed a prototypical implementation of a CBR-based RS, including a similarity function for case retrieval. The overall similarity of the problem parts of cases was defined as a weighted sum of local attribute-based similarities. Thus, a central problem was to define the weight that each local similarity should have in the sum. This was done by calculating the entropy, describing the degree of uncertainty in a system, of every attribute. The entropy was calculated by taking the attribute's values' relative frequency as a maximum likelihood estimation of a probability distribution p_i. The entropy

$$X = -\sum_i p_i \log(p_i) \quad (5)$$

then gives an indication of the information richness of the attribute – if nearly all cases in the case base have

the same value for an attribute, it is not very useful to separate relevant from irrelevant cases.
The weighting w_i was then simply calculated by taking the entropy value of each attribute and normalising it by dividing by the sum of all attribute entropy values. The attributes exhibiting the highest entropy weighting are:

1. Industry [$w = 0.149791516$]
2. Value proposition [$w = 0.127187279$]
3. Drivers [$w = 0.122342305$]
4. Strategic goals [$w = 0.108373204$]

From a business perspective, weighting the before-listed attributes the highest makes sense due to their significance when considering digital transformation. The industry most often indicates the development stage, meaning trends, maturity levels, and resources, of digitalisation activities, making it meaningful in the context of giving recommendations for digital transformation measures. On the other hand, the value proposition describes the products and services which create value for a specific customer segment. It is thus significant in indicating how companies with similar products and services have evolved and advanced in the context of digital transformation. The drivers as well as strategic goals not only indicate the direction of impact, but they are both strongly interlinked with the solution and the outcome of a digitalisation measure, making the condition of similarity very reasonable.

Since the case base, at this point, only consisted of 40 cases, it was enriched with an industry taxonomy (Bergmann, 2002). The industry taxonomy serves as additional knowledge which is integrated within the RS. The goal of the industry taxonomy is to be able to make recommendations for industries that are not represented in the case base yet, which are, however, similar to industries that are already represented. This will, eventually, lead to an improved result of the recommendations. The industry taxonomy was defined as shown in Table 3.

Various industries included in the NACE Rev. 1.1 classification list (Eurostat, 2015) were then allocated to level 1-3 classifications. The goal when defining these classifications was to be able to include not only traditional business models but business models that are emerging today. Thus, next to the rather traditional division of products and services, we integrated concepts such as technology creators as well as platforms that are very much present nowadays. In terms of services, we have added a level 3 classification, dividing the recipient of the service into people (such as hotels, restaurants and catering services) and things (like construction). Lastly, all of those classifications are supplied with a number, indicating the minimum similarity between two industries that are part of the same classification level. This is used for the computation of a local taxonomic similarity measure as proposed by Bergmann (2002). For example: all industries classified as asset builders have a minimum similarity of 0.6. The rationale behind this taxonomic approach is that two companies that are part of the asset builders' classification probably have a rather similar case for digital change since they share various important characteristics such as important business processes. In addition to defining an industry taxonomy, keywords for the various string attributes were extracted, which can be transferred between the different cases, to achieve better recommendation outcomes. For our rather small case base, this was done manually by the authors. As soon as the case base is growing, these keywords can, however, be extracted with the use of text mining methods, using e.g. Tf-idf or more sophisticated methods for keyword extraction (Lott, 2012). Lastly, the similarity measure of the attribute type "choice", which was most frequently used during this experiment, was based on the exact similarity of the two values, meaning zero (different values) or one (matching values).

Table 3: Industry taxonomy.

Level 1 classification	Level 2 classification	Level 3 classification
Asset builders (0.6)	Traditional asset builders (tangible) (0.7)	
	Technology creators (intangible) (0.3)	
Service providers (0.4)	Services (0.7)	People (0.6)
		Things (0.6)
	Platform (0.5)	

5.3 Test Run

The case model itself, with its various sets, relationships and attribute-value pairs was analysed and improved continuously throughout the project. Thus, this test run was performed merely to get a qualitative understanding of the output data that was generated by applying the defined case model and to showcase the added value of that model.

To get recommendations from the system, any company would need to provide information concerning the "general" and "problem" object. Thus, two experimental cases were defined to simulate a company wanting to receive recommendations. The case model is tested by running the prototypical case-based RS. The two scenarios were defined as follows:
1. The company can fill in all the company information and knows exactly what the drivers and strategic goals for the digital transformation are (maximum information provided). This case's information exactly

Table 4: Results from scenario one.

Case	Industry	Size	Age	Value	Customer segments	Bus. Relation	Cust. relation	Channel	Rev. streams	Key activity	Driver	Strategic Goal
1	Finance / Insu-rance	>= 250	>=5	Per-formance	Diversi-fied	B2C	Personal assistance	Own direct	Usage fee	Problem solving	Exploit new market	Digitali-sed bus. model
2	Finance / Insu-rance	>= 250	>=5	Get the job done	Segmen-ted	B2C	Self service	Own direct	Usage fee	Problem solving	Increase process efficiency	Cost advantage
3	Finance / Insu-rance	>= 250	>=5	Newness	Segmen-ted	B2C	Personal assistance	Own direct	Sub-scription fee	Problem solving	Exploit new market	Open up new market

represents an existing case from the case base. Thus, the case was subsequently removed from the case base. Its attribute values are as follows:

```
{INDUSTRY financial and insurance
sector, SIZE >=250, AGE >=5, VALUE
performance, CUSTOMER-SEGMENTS
segmented, BUSINESS-RELATION b2c,
CUSTOMER-RELATIONSHIPS personal
assistance, CHANNELS own direct,
REVENUE- STREAMS usage fee, KEY-
ACTIVITIES problem solving, DRIVERS
added value for employees, STRATEGIC-
GOALS optimise efficiency of employees}
```

2. The company cannot fill in all the company information and is not sure about the drivers and strategic goals for the digital transformation (minimum information provided). As we have omitted most attributes within this query, the case base was adjusted accordingly by removing those attributes.

```
{INDUSTRY financial and insurance
sector}
```

To conclude a meaningful result, it was necessary to compare the data to our assumptions. Firstly, we assume that our case model can be utilised by a case-based RS. Secondly, we assume that recommendations are ranked by similarity. The more information about a case is provided, the more closely the top-ranked cases should match this information. Based on these assumptions, we expect the following results for scenarios one and two:
1. For scenario one, we expect that the solution and outcome values of the cases within the financial and insurance sector are returned, with the ones which most exactly fit the input values ranked highest.
2. For scenario two, we expect that the solution and outcome values of all cases within the financial and insurance sector are returned in an arbitrary order.

5.4 Results and Discussion

For the results, there was no similarity threshold value set. The values most recommended by the RS, meaning the largest similarity scores, were registered first. We first explored the functionality of the case model in harmonisation with the RS by comparing the output data of the scenarios with the solution and outcome object of a case in the case base. Based on the output data we could recognise that the RS has given a recommendation for every necessary attribute. For every attribute, one to several values were provided. Thus, the basic functionality of the case model is guaranteed. We then examined the quality of the output data by comparing it to our expected results concerning the scenarios one and two. By quality, we mean that we expected that only the attribute-value pairs of a case in the case base would be returned in the top ranks which achieve a high similarity score regarding the test case. By weighting the attributes, the expectations for our scenarios were met fully. For query one, three cases were returned by the RS (table 4) while for query two, all the cases in the case base that featured the financial and insurance sector were returned. We can see here for instance that the case at rank 1 shares the value proposition with the query case while the others do not. It also shares customer relation and revenue streams values which are not shared by all other returned cases. Thus, the business model of Case 1 is significantly closer to the query case than that of Case 2 and Case 3. Although Case 1 might not be a perfect match to inspire the "input" company, it surely fits better than the other two – which qualitatively shows the value of a more elaborate case model.

Regardless of the above-mentioned successful results, we examined the task of structuring the cases by applying the case model. While building the case base, we have noticed that the task of structuring the cases is affected by the person's perception, meaning that the application of the case model is rather subjective. Further, we have looked at the recommendations from a user viewpoint. In the manner the recommendations are returned currently, we have realised that their interpretation may need prior knowledge of the case model, meaning that the logic would have to be extracted by the user him- or herself.

6 CONCLUSION

In this paper, we have developed a case model to structure cases of digital transformation that act as input data for the RS RoboInnocase. The case for digital change, which represents the output data of the RoboInnoCase, serves the inspiration phase of the management's initiatives concerning the company's own digital transformation. The output data of the RoboInnoCase contains recommendations concerning the possible area of the business transformation, how it could be transformed and the possible improvements of the change.

The case model of RoboInnoCase is defined along the four building blocks of the Transformation Compass, namely organisational excellence, customer centricity, operational excellence, and business model. Additionally, the results of the analysis of past cases of digital transformation constituted a further fundamental contribution to its definition. The final case model contains four sets, "general" (G), "problem" (P), "solution" (S), and "outcome" (O). Thus, each case is defined by the union of these nonoverlapping sets. The building blocks of the digital transformation are a central part of the "solution" set. The case model follows a hierarchical, object-oriented case representation, meaning that a case consists of various objects represented at numerous levels of detail which are each described by various attribute-value pairs.

Our results concerning the functionality of the case model as well as the quality of the given recommendations indicate that the case model is suitable to the needs of a case for change concerning digital business transformation. In terms of similarity, we weighted the most relevant attributes, calculated by the entropy, in a query higher than the remaining attributes. By doing so, the results that were returned were quite accurate. By implementing a first prototype of the RoboInnoCase, the assumptions made for both scenarios held true in the test run. Furthermore, the assumed exact similarity, achieved by weighting certain attributes differently, makes the given recommendations more accurate.

To improve the comprehensibility of the keywords in the solution, we suggest applying text mining methods as well as collecting a larger case base. Lastly, we highly recommend implementing a genuine form of RoboInnoCase which could then be customised to the proposed case model.

In this work, one could highlight the advantages of the RS for individual companies as well as serve as a basis for the creation of a model to define best practices.

REFERENCES

Aamodt, A., and Plaza, E. (1994). Case-based reasoning: Foundational issues, methodological variations, and system approaches. *AI Communications*, *7*(1), 39–59.

Aggarwal, C. C. (2016). Knowledge-based recommender systems. In *Recommender systems* (pp. 167–197). Springer.

Bergmann, R. (2002). *Experience Management: Foundations, Development Methodology, and Internet-Based Applications* (Vol. 2432). Berlin, Heidelberg: Springer.

Bergmann, R., Althoff, K.-D., Minor, M., Reichle, M., and Bach, K. (2009). *Case-Based Reasoning - Introduction and Recent Developments*. *Künstliche Intelligenz*. https://doi.org/10.1007/978-3-642-39056-2_1

Bergmann, R., Kolodner, J., and Plaza, E. (2005). Representation in case-based reasoning. *The Knowledge Engineering Review*, *00:0*(1–4), 1–4. https://doi.org/10.1017/S000000000000000

Bergmann, R., and Schaaf, M. (2003). Structural Case-Based Reasoning and Ontology-Based Knowledge Management: A Perfect Match? *Journal of Universal Computer Science*, *9*(7), 608–626.

Bridge, D., Göker, M. H., McGinty, L., and Smyth, B. (2005). Case-based recommender systems. *The Knowledge Engineering Review*, *20*(03), 315–320.

Choudhury, N., and Begum, S. A. (2016). A survey on case-based reasoning in medicine. *International Journal of Advanced Computer Science and Applications*, *7*(8), 136–144.

Dobni, C. B., Klassen, M., and Nelson, W. T. (2015). Innovation strategy in the US: top executives offer their views. *Journal of Business Strategy*, *36*(1), 3–13. Retrieved from https://www.emeraldinsight.com/doi/pdfplus/10.1108/JBS-12-2013-0115

Dr. Kraus and Partner. (n.d.). Case for Change - Definition. Retrieved November 24, 2018, from https://www.kraus-und-partner.de/wissen-und-co/wiki/case-for-change

El-Sappagh, S. H., and Elmogy, M. (2015). Case Based Reasoning: Case Representation Methodologies. *International Journal of Advanced Computer Science and Applications*, *6*(11), 192–208. https://doi.org/10.14569/IJACSA.2015.061126

Eurostat. (2015). Archive:Business economy by sector - NACE Rev. 1.1. Retrieved January 3, 2019, from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Business_economy_by_sector_-_NACE_Rev._1.1

Felfernig, A., and Burke, R. (2008). Constraint-based recommender systems: technologies and research issues.

In *Proceedings of the 10th international conference on Electronic commerce* (p. 3).

Furnas, G. W., Landauer, T. K., Gomez, L. M., and Dumais, S. T. (1987). The vocabulary problem in human-system communication. *Communications of the ACM*, *30*(11), 964–971.

Gable, G. (2003). Consultants and knowledge management. *Journal of Global Information Management*, *11*(3), i--i.

Gatziu Grivas, S., Peter, M., Heeb, D., Lanaia, A., Zimmermann, P., and Graf, M. (2018). The Panoramic Lens Model. In 2*018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*. IEEE, pp. 1–7. doi: 10.1109/ICE.2018.8436286.

Graf, M., Peter, M., and Gatziu Grivas, S. (2018). *Foster strategic Orientation in the Digital Age - A methodic approach for guiding SME to a Digital Transformation*. *IDEA*.

HWZ, and localsearch. (2018). Schweizer KMU fehlt es an digitalem Fachwissen – Digital Switzerland 2017. Retrieved October 12, 2018, from https://fh-hwz.ch/news/digital-switzerland-2017/

Jacoby, J. (2012). How to develop a powerful case for change. Retrieved November 24, 2018, from http://blog.emergentconsultants.com/2012/01/29/how-to-develop-a-powerful-case-for-change/

Jones, J., Aguirre, D., and Calderone, M. (2004). 10 principles of change management. Retrieved from https://www.strategy-business.com/article/rr00006?gko=643d0

Kolodner, J. L. (1991a). Improving Human Decision Making through Case-Based Decision Aiding. *AI Magazine*, *12*(2), 52–68. https://doi.org/10.1609/AIMAG.V12I2.895

Kolodner, J. L. (1991b). Improving Human Decision Making through Case-Based Decision Aiding. *AI Magazine*, *12*(2), 52–68. https://doi.org/10.1609/AIMAG.V12I2.895

Kolodner, J. L. (1992). An introduction to case-based reasoning. *Artificial Intelligence Review*, *6*(1), 3–34.

Lika, B., Kolomvatsos, K., and Hadjiefthymiades, S. (2014). Facing the cold start problem in recommender systems. *Expert Systems with Applications*, *41*(4), 2065–2073.

Lott, B. (2012). Survey of keyword extraction techniques. *UNM Education*, *50*.

Mansar, S. L., Marir, F., and Reijers, H. A. (2003). Case-based reasoning as a technique for knowledge management in business process redesign. *Electronic Journal on Knowledge Management*, *1*(2), 113–124.

Nissen, V., and Seifert, H. (2017). Die digitale Transformation der Unternehmensberatung. In *Dienstleistungen 4.0* (pp. 411–443). Springer.

Osterwalder, A., Pigneur, Y., Oliveira, M. A.-Y., and Ferreira, J. J. P. (2011). Business Model Generation: A handbook for visionaries, game changers and challengers. *African Journal of Business Management*, *5*(7), 22–30.

Pazzani, M. J., and Billsus, D. (2007). Content-based recommendation systems. In *The adaptive web* (pp. 325–341). Springer.

Peter, M., Graf, M., Gatziu Grivas, S., and Giovanoli, C. (2018). Die ABILI-Methodik : Inspiration und Navigation bei der Digitalen Transformation mit Fokus auf KMU. *Arbeitsberichte Der Hochschule Für Wirtschaft FHNW*, (36), 1–17. Retrieved from https://kmu-transformation.ch/die-abili-methodik-inspiration-und-navigation-bei-der-digitalen-transformation-mit-fokus-auf-kmu/

PwC Schweiz. (2016). *Digitalisierung-wo stehen Schweizer KMU?* Retrieved from https://www.pwc.ch/de/publications/2016/pwc_digitalisierung_wo_stehen_schweizer_kmu.pdf

Ricci, F., Rokach, L., and Shapira, B. (2011). Introduction to Recommender Systems. In *Recommender Systems Handbook* (Vol. 532, pp. 1–35). Springer Science + Business Media. https://doi.org/10.1007/978-0-387-85820-3

Rissland, E. L., Ashley, K. D., and Branting, L. K. (2005). Case-based reasoning and law. *The Knowledge Engineering Review*, *20*(3), 293–298.

Schafer, J. Ben, Frankowski, D., Herlocker, J., and Sen, S. (2007). Collaborative filtering recommender systems. In *The adaptive web* (pp. 291–324). Springer.

The Change Source. (2013). How to build a case for change. Retrieved November 24, 2018, from https://de.slideshare.net/thechangesource/how-to-build-a-case-for-change

Tiihonen, J., and Felfernig, A. (2010). Towards recommending configurable offerings. *International Journal of Mass Customisation*, *3*(4), 389–406.

Vaishnavi, V., and Kuechler, W. (2004). Design Research in Information Systems - Overview of Design Science Research. *AIS*, 45.

Westerman, G., Calméjane, C., Bonnet, D., Ferraris, P., and McAfee, A. (2011). *Digital Transformation: A Road-Map for Billion-Dollar Organizations*. *Capgemini Consulting & MIT Sloan Management*. Retrieved from https://www.capgemini.com/wp-content/uploads/2017/07/Digital_Transformation__A_Road-Map_for_Billion-Dollar_Organizations.pdf

Witschel, H. F., and Martin, A. (2018a). *Random Walks on Human Knowledge: Incorporating Human Knowledge into Data-Driven Recommenders*. Retrieved from http://insticc.org/node/TechnicalProgram/ic3k/presentationDetails/68939

Witschel, H. F., and Martin, A. (2018b). *Random Walks on Human Knowledge: Incorporating Human Knowledge into Data-Driven Recommenders*.