UNIVERSITY OF TWENTE.

Faculty of Behavioural
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Exploring the effects of HR Analytics on Strategic Decision Making

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September 2019

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Abstract

Through three case studies on HR analytics processes, the enactment of Strategic Decision Making characteristics by HR analytics is uncovered. A new unified framework is presented in which the HR analytics process is integrated with the strategic decision-making process. Moreover, the contextual influences of intellectual capital, institutional isomorphism and e-HRM on this framework have been identified. With these discoveries, the variance in successful outcomes between HR analytics practices can be explained, providing HR analytics practitioners insight into what can make or break an HR analytics process.

1 Introduction

Data flows through every organisation, across multiple departments, and is at the centre of success for some of the largest contemporary organisations, such as Google, Amazon and Facebook. Professionals in various fields are confirming the importance of data for the business, and rightfully so, as data-driven decision making is positively associated with profitability, productivity and market value (Brynjolfsson et al., 2011). For the field of HRM, analytics is seen as an essential skill for HR professionals, as HR analytics is suggested to increase the credibility of the HR department by enabling the ability to quantify the contribution of practices and policies to strategic initiatives, as well as expose practices and policies that do not contribute to their respective intended outcomes (Bassi, 2011; Mondore et al., 2011; Rasmussen and Ulrich, 2015). However, realising the potential of HR analytics seems to by a difficult task, and various studies have stated a similar sentiment when criticising the state of HR analytics: a change in how to 'do' HR analytics is required (Angrave et al., 2016; Rasmussen and Ulrich, 2015; Mondore et al., 2011).

HR analytics has been in different manners, such as "the systematic identification and quantification of the people drivers of business outcomes, with the purpose of making better decisions" (Van den Heuvel and Bondarouk, 2017) or "A HR practice enabled by information technology that uses descriptive, visual, and statistical analyses of data related to HR processes, human capital, organizational performance, and external economic benchmarks to establish business impact and enable data-driven decision-making" (Marler and Boudreau, 2017). These definitions introduce two interesting elements. First, it implies that HR analytics is a process that utilises a quantification of people-related data that led to certain business outcomes. Second, it is stated that the goal of this quantification is improved decision making. In this definition, HR analytics outcomes are decisions, and the process to achieve these outcomes is the identification and quantification of people-related data leading to business outcomes.

Several studies have already investigated phenomena affecting the performance of the HR analytics process. The study on HR analytics by Rasmussen and Ulrich (2015) provides various suggestions based on existing practices to improve the state of HR analytics in organisations by focusing on capability building, whilst Angrave et al. (2016) points out that the tools and services used in HR analytics affect the state of the HR analytics and a different approach is required in how we select and use these tools. Others point out the importance of the methods of data collection for the advancement of HR analytics, such as the use of longitudinal studies and good enterprise-wide surveys (Guest, 2011; Wall and Wood, 2005). Finally, Marler and Boudreau (2017) performed a literature review and compressed existing knowledge on HR analytics by describing three moderating factors that affect the impact of the HR analytics process on HR analytics outcomes: 1) the analytical skills of HR analytics practitioners, 2) the Network of supportive stakeholders across the company hierarchy and 3) the quality and accessibility of the data and capabilities of the e-HRM software system.

Whilst various phenomena are described that affect HR analytics practices and their outcomes, it remains unclear *how* these phenomena affect HR analytics and its outcomes. Moreover, Marler and Boudreau (2017) calls for a unified framework for HR analytics, empirical evidence for the business impact of HR analytics and studies into the slow diffusion of HR analytics within organisations. This study attempts to solve these issues by describing how HR analytics as a process enacts characteristics in the strategic decision-making process by performing an explorative, qualitative study within an HR analytics practice of a large national Telecom Company. In summary, this study attempts to answer the question:

What characteristics of Strategic Decision Making are enacted by HR analytics?

This study introduces literature related to 1) the conceptualisations of data, information and knowledge, 2) the Strategic Decision Making Process, 3) HR analytics, 4) Intellectual Capital and 5) e-HRM, to build a conceptual framework on how the HR analytics process affects the SDM process. This serves as a point of departure for the qualitative study in which this conceptualisation is further explored using three separate case studies at a large national Telecom Company.

In the end, the findings from these case studies are integrated to create an understanding on how the characteristics of Strategic Decision Making are enacted by an HR analytics process, as well as how external influences can affect this enactment. This provides HR analytics practitioners with guidelines on how to improve practices to improve HR analytics outcomes.

2 Literature Review

In this section, a variety of literature related to the SDM process as well as HR analytics is introduced. First, conceptualisations of data, information and knowledge are described to set up the link between HR analytics and the SDM process. Second, the characteristics of the SDM process are evaluated, involving decision phases, routines and external influences. Third, the concept of HR analytics is dissected and described as a process that aids the SDM process on HR systems. Fourth, the concept of intellectual capital is introduced to describe the various type of knowledge that exists within the organisation. Fifth, the concept of e-HRM is introduced to investigate the potential influence of technology on the HR analytics process. Finally, a conceptual framework is described that describes the link between HR analytics and the SDM process and the impact on HR systems, which will be used as a point of departure to qualitatively investigate how these SDM characteristics are enacted by HR analytics, and how external factors might interrupt this enactment.

2.1 Data, Information & Knowledge

Various definitions of the relationship between data, information and knowledge have been created across various scientific domains. In this section, the various interpretations are explored to define how data can be transformed into knowledge that can aid in making a decision. To do this, the attempt of Zins (2007) to define data, information and knowledge to explore the foundation of information science is utilised. These definitions are based on an extensive study on an international and intercultural panel of 57 participants of 16 countries using the Critical Delphi methodology.

First, Zins (2007) take on the definition is used to introduce several relevant concepts. Zins (2007) defines data, information and knowledge in the context of inferential propositional knowledge. This type of knowledge stems from one of the three types of knowledge that stem from traditional epistemology. These three types are practical knowledge, knowledge by acquaintance and propositional knowledge (Bernecker and Dretske, 2000). Practical knowledge relates to skill, such functional abilities like balancing a soccer ball. Knowledge by acquaintance involves direct recognition of external objects, like a specific bird, or inner phenomena, such as pain or hunger. *Propositional knowledge* is the reflection of a person on what he/she knows. It implies that thoughts are expressed as propositions. This type of knowledge can, in turn, be separated in inferential and non-inferential knowledge. Non-inferential propositional knowledge states an intuitive understanding of a phenomenon, 'this is true innovation'. *Inferential propositional knowledge* is a result of inferences such as deduction and induction, 'this is a seagull because it is white and near the sea'.

Moreover, Zins (2007) states that there are two different conceptualisations for data, information and knowledge, totalling six concepts. These two sets are separated by the domains of subjective knowledge and universal knowledge. *Subjective knowledge* is the knowledge that exists within an individual, such as thoughts, whereas *universal knowledge*, or objective knowledge, is knowledge existing in the external world, such as articles.

In the *subjective domain*, *data* are sensory stimuli or their meaning, such as noise and the perception that this noise results from a blowing fan. *Information* is empirical knowledge, the fan is on and blowing air. This means that information is already a type of inferential propositional knowledge, and not an intermediate stage between data and knowledge, within this domain. *Knowledge* can be seen as a thought in an individuals mind, which is the justifiable belief that the information is true. This is different from knowing, which means that the individual believes the observation is true, it can be justified and it is true, or appears to be. (Zins, 2007)

In the *universal domain*, data, information and knowledge are human artefacts, represented by empirical signs (digital signals, words, sound waves, light beams, signs that a human can perceive through its senses). In this domain, *data* is a set of signs representing empirical stimuli or senses, *information* is a set of signs which represent empirical knowledge and *knowledge* is a set of signs that represents a meaning or the context of thoughts that an individual perceives as true. Whilst signs represent a meaning, meaning itself cannot be perceived from signs directly. (Zins, 2007)

To contrast this definition, the definition of data, information and knowledge in the context of the organisation by Davenport et al. (1998) is introduced. Here, Data is described as a set of discrete, objective facts about events, usually described as structured records of transactions (Davenport et al., 1998). Information is described as a message, transferred in the form of a document or communication, and is meant to shape the way data is perceived (Davenport et al., 1998). If this information can be viewed as interesting and certain enough by an end-user, who can interpret this using a mix of experience, values, more contextual information and expert insight, the information can transform into knowledge by adding a human interpretation to the information (Davenport et al., 1998; Frawley et al., 1992).

Zins (2007) found that five different conceptual models existed in the expert panel of the study. To develop these models, Zins (2007) focused on a non-metaphysical and human-centred approach, with the human approach involving a choice to approach the models as cognitive-based and propositional, with a separation between subjective and objective domains. Taking a cognitive-based approach means that humans act on more than just physical phenomena and utilise conscious thoughts to act. The five models state if data, information and knowledge respectively fall under the universal domain, subjective domain or both. Within these models, Davenport et al. (1998) would fall under the most popular one under the panel seeing data and information as universal, and knowledge as subjective, where data and information are both seen as signs and knowledge as human interpretation.

In conclusion, this study will adopt the same approach to data, information and knowledge as Zins (2007), meaning that a non-metaphysical, human-centred, cognitive-based and propositional approach, whilst acknowledging that data, information and knowledge can exist in both the subjective as well as the objective domain. This allows for a logical transformation of data into knowledge both on an individual and organisational level. In the following section, the SDM process will be described, which will describe how knowledge can be used during the SDM process.

Later, the conceptualisation of HR analytics will describe how this transformation of data into knowledge can exist in the HR domain.

2.2 The Strategic Decision-Making (SDM) Process

In the introduction, HR analytics outcomes are described as an improvement in decision making. Without decisions as a result of HR analytics, HR analytics remains the mere extraction of information from data, without producing knowledge that can provide the firm with a competitive advantage. To evaluate how the HR analytics process can influence HR analytics outcomes, the process of decision making should be understood and defined.

2.2.1 Decisions and HR analytics

Within the domain of HR analytics, the *LAMP* framework and the *HR scorecard* are described as a framework to aid in the discovery of evidence-based relationships to improve strategic decision-making (Boudreau and Ramstad, 2007). Whilst these discuss several means to evaluate the impact of HRM operation and investment in these operations on strategic business outcomes, the decision making the process as a result of HR analytics processes using these framework remains.

Few studies attempted to describe the impact of HR analytics on business outcomes. Aral et al. (2012) found the direct impact of the practice of performance pay, HR analytics and Information Technology on decision making in managers and employees using principal-agent theory. Within this interplay of tools, processes and practices in the HRM domain, HR analytics enabled by information technology provided an incentive for the agent to act due to the visibility of performance in parallel with the HR practice of performance pay. Harris et al. (2011) describes several cases studies that show how several organisations apply HR analytics to improve decision making in recruitment and to improve employee engagement to achieve an increased positive impact on strategic business outcomes. Moreover, Harris et al. (2011) shows that investing in HR analytics tools can improve business outcomes.

Whilst these studies validate that HR analytics can impact organisational performance by improving decisions, both lack a clear description of how the decision-making process was affected by HR analytics practices. Moreover, Harris et al. (2011) formulates HR analytics as a tool or technology. This study, however, views technology as a mere enabler for the process of HR analytics, as technology on its own does not lead to knowledge that can aid decisions. Angrave et al. (2016) states that data-driven decision making occurs when "analytics show that a particular policy or approach brings about improvements in performance and that there is a significant return on improved performance". Whilst this comes close to how this study desires to approach HR analytics, this merely describes one possible decision moment. In this study, the conceptualisation of the Strategic Decision Making (SDM) process by Mintzberg et al. (1976) is utilised to develop a framework that can aid in describing how HR analytics can affect the entire process of decision making in concert, instead of at one point.

2.2.2 A general SDM process model

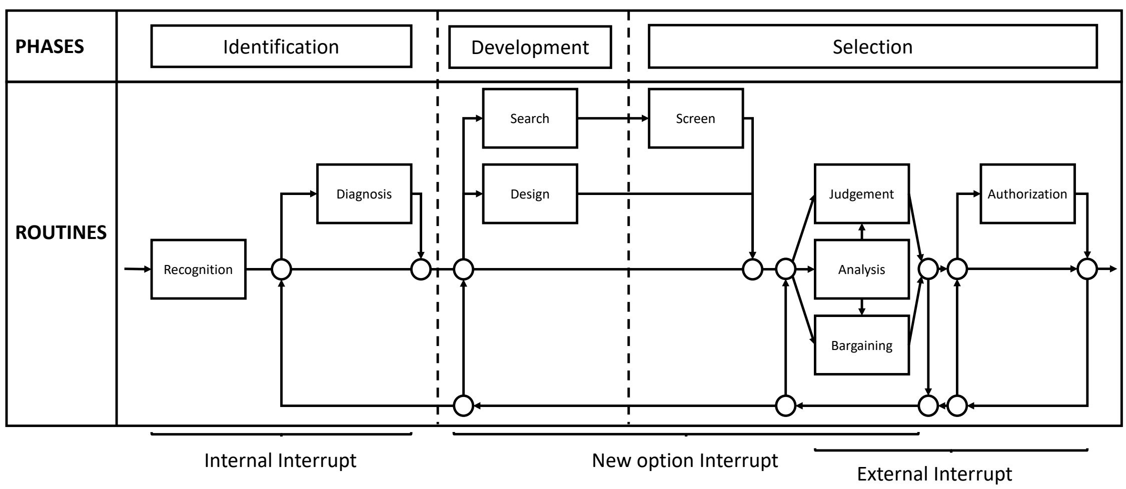
Mintzberg et al. (1976) attempted to model the unstructured strategic decision-making process using 25 case studies in decision processes. Here, a *decision* is as a specific commitment to action, and a *decision process* is a set of actions and dynamic factors that begins with the identification of a stimulus for action and ends with the specific commitment to action. Moreover, *unstructured* refers to decision processes that have not been encountered in the same form and for which no predetermined and explicit set of ordered responses exist in the organisation, and *strategic* means that the decision is linked to business outcomes and resources are allocated (Mintzberg et al., 1976).

Utilising a decision process has been shown to have a significant effect on strategic decision making effectiveness, where procedural rationality had a positive reinforcing effect (Dean Jr and Sharfman, 1996). *Strategic decision* effectiveness is as "the extent to which a decision achieves the objectives established by management at the time it is made" (Dean Jr and Sharfman, 1996). *Procedural rationality* is as "the extent to which the decision process involves the collection of information relevant to the decision and the reliance upon analysis of this information in making a choice (Dean Jr and Sharfman, 1993). This is based on the *rational normative model* which assumes that "strategic decision making involves sequential, rational and analytical processes whereby a set of objective criteria are used to evaluate strategic alternatives" (Hitt and Tyler, 1991; Huff and Reger, 1987; Ackoff, 1981; Igor Ansoff, 1986; Camillus, 1982). Hitt and Tyler (1991) found that 82% of the variance in executive decision making was based on objective criteria, but also found support for the upper echelons theory, which states the importance of managerial characteristics on strategic choices in an organisation (Hambrick and Mason, 1984). Thus HR analytics can have a positive effect on strategic decision making but is not the only factor that plays a role in strategic choice as this is also affected by other factors such as managerial characteristics, politics and industry factors (Dean Jr and Sharfman, 1996; Hitt and Tyler, 1991; Hambrick and Mason, 1984; Mintzberg et al., 1976). Therefore, to evaluate improved decision making as a consequence of HR analytics, external factors should be taken into account.

As stated before, because strategic decision choices exist in a larger strategic decision process, the potential impact of HR analytics should not just be evaluated at one choice, but during the entire process. Mintzberg et al. (1976) describes several phases based on phase theorem by Witte et al. (1972). A phase represents an element of the decision-making process. These phases are described as *Identification*, *Development* and *Selection.* In turn, these phases consist of various routines. To describe the influence HR analytics can have on the SDM process, it is important to describe these various elements of the SDM process. An overview of the SDM process as described by Mintzberg et al. (1976) can be found in figure 1.

The *Identification Phase* consists of the recognition routine and the diagnosis routine. The *Recognition routine* consists of the identification of an issue and making the choice to continue the decision making process on this issue or not. The decision in this routine arises from the difference between the information on a situation and

Figure 1: *A general model of the SDM process as described by Mintzberg et al. (1976).*



the expected standard for this situation. The expected standards are based on past trends, projected trends, industry standards, expectations of other people and theoretical models (Pounds, 1965). The data that decision-makers receive to assess if the expectations are met and if there is a problem, crisis or opportunity related to the mismatch, often arrives as ambiguous, largely verbal data (Mintzberg et al., 1976; Sayles, 1964).

The *Diagnosis Routine* comes after the recognition of a problem and the identification of a scoping issue and results in an action that determines the scope of the problem identified in the recognition routine. Mintzberg et al. (1976) describes this routine as consisting of accessing existing information sources and opening of new ones to clarify and define the issue at hand. It expands on the recognition phase, where a certain stimulus is detected. Careful diagnosis is not always executed during decision making, something that is argued to separate Japanese decision-makers from American ones (Drucker, 1971). Whilst diagnosis can be skipped when time is stringent, properly scoping the issue at hand can prevent final solutions that only treat part of the problem at hand, or cause new problems all together (Rogers, 2010; Wieringa, 2014).

The *Development Phase* is split between two routines, search and design, based on the concept of divergent and convergent thinking. By searching, one finds various solutions and attempts to converge these into one. By design, one creates various solutions from a single idea, diverging from one solution to many.

The *Search Routine* consists of four characteristic behaviours (Mintzberg et al., 1976). 1) Memory search is scanning of existing memory, human or paper. 2) Passive search is waiting for alternative solutions to appear. Think for example about start-ups looking for an opportunity to develop their solution at large organisations. 3) Trap search involves invoking 'search generators' to produce alternatives, such as invoking external suppliers by letting them know the organisation is looking for a solution for a certain problem (Soelberg, 1966). 4) An active search is the direct seeking of alternatives, by either looking wide or narrow at available options (Newell et al., 1972).

The *Design Routine* consists of either new or adapted solutions. Adapted solutions are solutions derived from the search routine which are deemed suitable but still require some adaptation to fit the scope of the problem. The design process is iterative, consisting of searching for solutions, finding the best options and selecting how to continue with the design process until a solution is achieved. (Mintzberg et al., 1976) found that from the 14 decision cases in the study which involved a custom-design routine, in all cases only one single solution was fully developed. In three modifications of existing solutions which involved a custom design, multiple solutions were developed. Reasons for this are the high resource costs related to developing multiple solutions compared to the relative cheap search routine.

Decisions in the design routine did not consist of conflicting alternatives, but a choice for a specific course of action. This fits the design science methodology by Wieringa (2014), where the development of one solution requires one design cycle; multiple solutions require multiple, separate design cycles. This is due to the search preceding the design phase, which should determine the right alternative from many options to develop a design upon.

The *Selection Phase* is often the final stage of the decision process but often iterates back to the development process, as the development process tends to spawn several decisions requiring at least one selection step. Mintzberg et al. (1976) found the selection phase to first consists of a screening routine that decreased a large number of alternatives spawned from the search routine. Afterwards, an evaluation-choice routine occurs, where these alternatives are assessed and a single course of action is chosen. This evaluation-choice routine also consists of several subroutines, such as Judgement, Analysis and Bargaining. Finally, an authorisation routine can be invoked to process the course of action through the required level of the organisational hierarchy.

The *Screen Routine* is often a superficial process that eliminates infeasible alternatives that spawned from the search process. Where the search routine looks for alternatives that will aid the problem scope, the screening routine determines the appropriateness of the alternatives to the organisational context, but also reduce the number of alternatives due to time constraints. The screen routine is almost always implied with the search routine, and whilst screening often is a quick process, it remains a separate type of decision. (Mintzberg et al., 1976)

The *Evaluation-choice routine* involves three different modes. *Judgement* involves an evaluation by an individual that chooses its own without any explanation. *Bargaining* involves a selection by a group of individuals who all make their won judgement. *Analysis* involves a factual evaluation of the choice at hand, which is followed by judgement or bargaining. Interesting in the context of this study, whilst normative literature suggests the importance of analysis, Mintzberg et al. (1976) found very little use of an analytic approach in the case studies. Often, a judgement formed the preferred mode of selection due to its efficiency.

The evaluation-choice routine utilises mostly non-quantitative factors opposed to quantitative factors (Mintzberg et al., 1976). Moreover, a variety of elements affect the evaluation-choice routine, such as emotions, politics, power, personality, cognitive limitations due to information overload and bias (Snyder and Paige, 1958; Newell et al., 1972; Soelberg, 1966). This routine is especially interesting in the context of this study, as data-driven decision making is often mentioned only in the context of selection of alternatives and is essentially embedded in the analysis routine.

The *Authorization Routine* are required when an individual does not have the authority to commit the organisation to an action (Mintzberg et al., 1976). Most often, authorisation is sought after a final solution has been developed after a set of evaluation-choice routines and development iterations. Issues at this routine are often related to the lack of knowledge available to the authority figure that has to make a decision, and the lack of time to evaluate the proper course of action. These processes tend to be less analytical than suggested by normative literature (Carter, 1971b,a; Bower, 1970).

Mintzberg et al. (1976) also describes three supporting routines that help the decision process, such as the decision control routine to help the process of making a choice, the communication routine to provide input and output of information in the decision making and political routines that allow decisions to be made in an environment of various influences, sometimes hostile. Moreover, there are dynamic factors described that influence the decision-making process, such as interruptions, scheduling delays, feedback delays time delays or speedups, comprehension cycles and failure recycles.

Overall, these routines, supporting routines and dynamic factors generate the model as presented in figure 1, where the routines and the possible flows through these routines are visualised as done by Mintzberg et al. (1976). This model allows us to operationalise the decision-making process during qualitative research, as flows, routines and dynamic factors can be classified and evaluated for a specific case. Consequentially, this allows the investigation of how HR analytics enacts these characteristics of the SDM process.

2.3 HR Analytics

To investigate the enactment of SDM characteristics by HR Analytics, the process of HR analytics has to be described. This section does this in two ways. First, a working definition for HR Analytics is created in the context of the conceptualisations of data, information and knowledge by Zins (2007) and the SDM process. Here, the relationship between data, information, knowledge and the SDM process is described in an abstract manner and seen as the overall concept of HR analytics. Second, the activities that shape the HR analytics process are clarified and defined. This contains the praxis of HR analytics and allows for the investigation for factors that influence these activities and can lead to a deviation in how HR analytics enacts the characteristics of the SDM process.

2.3.1 Defining HR analytics

This study approaches the concept of HR analytics as a process that leads to better strategic decisions within HRM. This means that the strategic decision-making process in some way is related to the shaping of the HR system. The *HR system* is as a program within an organisation that consists of multiple HR policies that are inclined to be consistent with each other and try to achieve a common goal that improves strategic business goals. *HR policies* in turn reflect employee-centred programmes that influence the type of HR practices that are used within an organisation. *HR practices* reflect the actions taken to achieve the outcomes intended by the HR policies. (Lepak et al., 2006; Becker and Gerhart, 1996; Schuler, 1992)

To develop a working definition, the highest level of abstraction for HR activities is utilised, which is the HR system. HR system influence the individual employee performance, which consequently makes up the collective employee performance, which leads to the overall organisational performance (Lepak et al., 2006). Moreover, in the model by Lepak et al. (2006), the organisational performance is seen as a driver for the strategic focus, and the HR system is in turn driven by this strategic focus. An SDM process as conceptualised by Mintzberg et al. (1976) starts with a recognition routine, which is triggered when a certain threshold is met in terms of a deviation of the expected performance of the business and the actual performance of the business. At the end of the strategic decision-making process, a strategic focus is developed, which in turn can lead to improvements in the HR system. Thus, the SDM process is seen as the intermediary process that determines a new strategic focus from which HR systems can be derived.

To link the HR analytics process to better strategic decisions, the conceptualisation of data, information and knowledge by Zins (2007) is used, where knowledge is seen as the end product of the HR analytics process, which in turn can be used to inform the SDM process. In this context, the knowledge that can aid the SDM process is inferential propositional knowledge, which can be derived from information in the form of both deduction and induction. During induction, knowledge is derived from information by observing patterns that emerge from data and developing a theory about these patterns. During deduction, a theory or hypothesis already exists, and the goal is to confirm this hypothesis or theory from information to validate and interpret this hypothesis, creating new knowledge.

Taking the transformation from data into knowledge through either deduction or induction into account, as well as the way this can inform SDM processes which in turn can affect HR systems and organisational performance, HR analytics is as:

"A process that concerns the deduction and induction of knowledge using data related to people, to improve the effectiveness of the strategic decision making process on the strategic focus for the HR system."

2.3.2 The HR Analytics Process

To evaluate HR analytics, the activities that enable the transformation from data to knowledge to aid the SDM process on HR systems have to be identified. These activities contain the praxis of HR analytics, which has been noted to be missing in a vast amount of HR analytics literature (Marler and Boudreau, 2017; Angrave et al., 2016). In HR analytics, the praxis of HR analytics has been described as the "rigorously tracking of HR investments and outcomes" (Ulrich and Dulebohn, 2015) or as "statistical techniques and experimental approaches that can be used to tease out the causal relationship" (Lawler III et al., 2004) to achieve better decisions on HR systems.

The first statement on the praxis of HR analytics by Ulrich and Dulebohn (2015) about tracking HR investments and outcomes concerns the identification and quantification of people data from the definition of HR analytics by Ruel et al. (2007). The identification and quantification of people data can be seen as activities that create the data on which an analysis can be performed. In the context of subjective and universal data, the *identification* activity is seen as finding subjective data that can aid the creation of knowledge that can aid the SDM process, and the *quantification* activity is seen as developing a way to transform this subjective data into universal data from which information can be derived from statistical techniques.

The second statement on statistical techniques and experimental approaches by Lawler III et al. (2004) is more closely related to the process of transforming quantitative data into information. To derive the activities that enable this process, the field of knowledge discovery in databases (KDD) is utilised. KDD is as "the non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data" (Fayyad et al., 1996).

KDD describes various steps to move from digital universal data towards knowledge (Fayyad et al., 1996; Brachman and Anand, 1996). In total, 9 steps are described by the KDD process as per Fayyad et al. (1996), which can be distilled into 7 activities: 1) Inquiry, 2) Selection, 3) Preprocessing, 4) Transformation, 5) Data Mining, 6) Interpretation and 7) Informing. Besides, the concept of HR metrics, which will be introduced below, is seen as a separate activity that can speed up the transformation from data to knowledge.

The *Inquiry activity* consists of receiving a request from a business stakeholder for certain knowledge on an issue. Based on this request, a context and knowledge gap should be identified and documented (Fayyad et al., 1996). This forms the way an SDM process routine can initiate an HR analytics process to aid the routine and determining the correct course of action. Note that it is not unthinkable that there is no real knowledge gap within the organisation, which can occur when the knowledge required by the SDM process can already be induced or deduced from available information through the interpretation activity. In this situation, the HR analytics process can already inform the SDM process with appropriate knowledge. Therefore, we state that the interpretation activity is triggered by this activity after which other activities in the HR analytics progress can be triggered

The *Selection activity* has the goal of creating a target dataset to perform the knowledge discovery process on. Here, one defines which variables or constructs are required to solve the knowledge gap (Fayyad et al., 1996). If no universal data is available, the identification and quantification activities are required to gain the required universal data from subjective data.

The *Preprocessing activity* concerns both cleaning the data by removing noise, dealing with missing data and preprocessing by accounting for time sequence information and known changes that can affect the statistical analysis (Fayyad et al., 1996). At this point, continue with the next activity, concerning the transformation of data and statistical analysis or data mining to derive patterns that construct the information useful to derive knowledge. However, another important phenomenon exists that is often mentioned alongside HR analytics, which is HR metrics.

HR metrics are used to assess HR on three levels: efficiency of operations, the value of human capital and the effectiveness of HR practices and policies or impact of HR practices and policies (Dulebohn and Johnson, 2013; Lawler III et al., 2004). Dulebohn and Johnson (2013) also mentions a fourth level of HR metrics, which is the strategic HR metric, linking business outcomes with HR practices and policies. However, this is where we separate HR metrics and HR analytics. Analytics are used to derive more than ratios and discover causal links between metrics and strategic decisions (Ruel et al., 2007; Lawler III et al., 2004). However, metrics can already provide interpretable information that can aid the strategic decision-making process in the form of ratios. For example, through metrics, one can find that absenteeism, a ratio, has risen compared to last year. This can initiate the search for a causal link through analytics. In sum, preprocessed data can be transformed by developing HR metrics into information. HR metrics are seen as an activity that might occur within the praxis of HR analytics to derive information at an early stage in the entire HR analytics process.

The *Tranformation activity* involves finding useful features that represent the data to solve the knowledge gap. This involves reducing the number of variables to find invariant representations of data (Fayyad et al., 1996). Examples of techniques that occur during the transformation activity are Z-score normalisation, dealing with the skewness of data, log-normalisation and dealing with outliers.

The *Data Mining* activity involves several steps and consists of the statistical techniques to discover patterns within data. First, a statistical technique needs to be selected that can provide information useful for solving the knowledge gap, such as clustering, regression, classification, summarization or others (Fayyad et al., 1996). Then, the correct algorithms or applications of these statistical techniques have to be selected to derive useful patterns from the transformed data. This is important in the context of the 'no-free-lunch' theorem, which states that there cannot be a best practice algorithm or application of statistical techniques for all types of sparse data (Xu et al., 2011). Finally, one executes the selected algorithm or application to derive patterns or information from the dataset. This information exists in both the subjective as well as the universal domain: empirical relations are made (regarded as subjective) and it is represented in interpretable signs and symbols (regarded as universal). The *Interpretation activity* involves the transformation of the derived patterns or ratios into knowledge by applying human experience, values and norms. If this does not sufficiently fill the knowledge gap, one is ought to step back to one of the previous activities, starting from selection, until the knowledge required knowledge is discovered. The knowledge can be derived through either induction or deduction.

The final activity is the *Informing activity* which provides the knowledge gained during the HR analytics process back to the SDM process. Following Zins (2007) conceptualisation, this will be done by transforming the subjective knowledge of the HR analyst back into universal knowledge, interpretable by the people involved in the SDM routine to determine a course of action.

2.3.3 A model for HR analytics

Using the definition of HR analytics and the activities above, an ideal model of HR analytics can be created that captures the entire HR analytics process in terms of constructs, activities flows between activities guided by activities and triggers for activities, based on the description of the HR analytics process in the previous section. This is visualised in figure 2.

Here, we make the distinction between the subjective and universal domain on the data and knowledge level, but not on the information level; the information resulting from the HR analytics process exists in both domains, as it is empirical and presented in symbols; the transformation from universal data to pure subjective information is possible within the boundaries of Zins (2007) conceptualisation, for example when someone makes an inference entirely in the mind objectively without telling anyone about the process. Logically, this is not expected to happen during an analytical process. Therefore, information is not split between universal and subjective domains, but is regarded as both simultaneously when stating 'information'.

Thus far, a general model for SDM by Mintzberg et al. (1976) has been introduced and an ideal model has been created for HR analytics, where the HR analytics process feeds the SDM process with the knowledge to make informed decisions about the HR system. However, the concepts of data, information and knowledge within the organisation have yet to be described. Most activities that transform universal data into information leverage some form of algorithm or application, requiring technology. To investigate this, the concept of e-HRM is introduced. First, however, this study will introduce the concept of intellectual capital, which gives more depth to various forms in which knowledge exists within organisations.

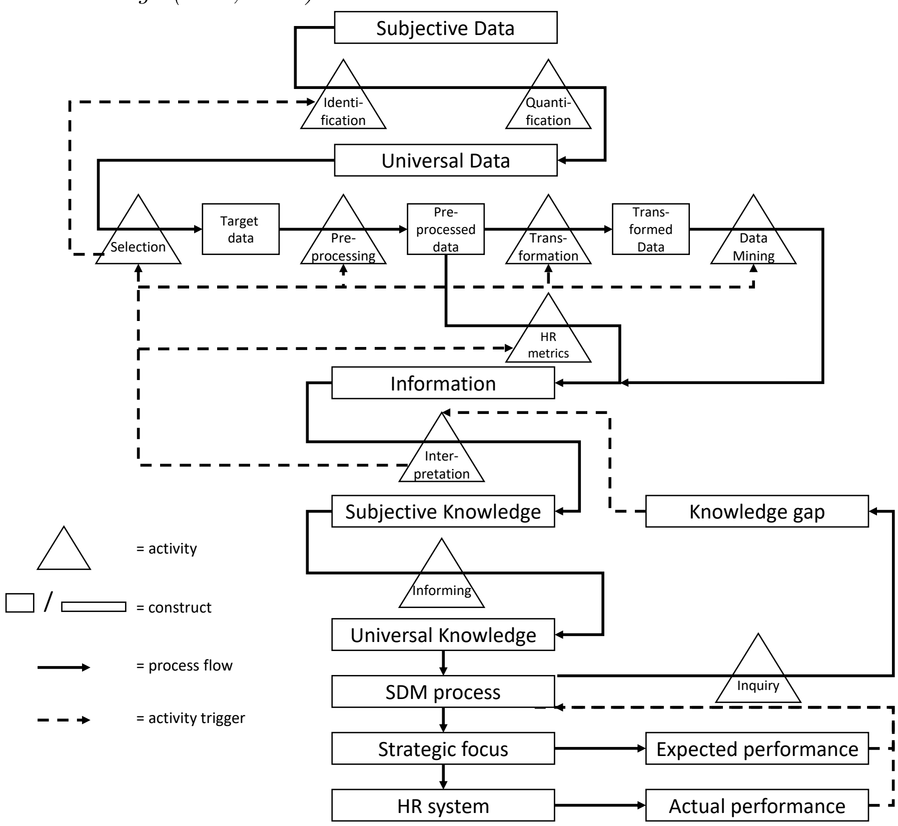
2.4 Intellectual Capital

Intellectual Capital can refer to "the knowledge and knowing capability of a social collective, such as an organisation, intellectual community or professional practice" (Nahapiet and Ghoshal, 1998). This concept involves both the concept of value appropriation (knowing), as well as value creation (knowledge) (Di Gregorio, 2013; Nahapiet and Ghoshal, 1998; Moran and Ghoshal, 1996). Value creation is seen as actions that lead to novel combinations and exchange of resources, where resources are utilised and deployed in a new context, outside of known applications (Schumpeter, 1928). Value appropriation consists of two types, inter-organizational and intra-organizational. Inter-organizational value appropriation involves capturing created value in resources within the firm, therefore securing value away from other firms (Di Gregorio, 2013; Barney et al., 2001; Barney, 1991). Intra-organizational value appropriation can be seen as the capturing of value by various stakeholders within the organisation (Di Gregorio, 2013). In this conceptualisation of value, knowledge as a value can be created by an organisation, captured from the environment, and thus from other organisations and spread throughout the organisation.

In the context of the HR analytics process presented in figure 2, the knowledge output of HR analytics is created value from essentially subjective data. The 'knowing' within the organisation, or the appropriation of knowledge as a value, can be seen as a factor that affects the quality of HR analytics activities.

To clarify the relationship between the creation of knowledge and the appropriation of knowledge, the concept of intelligence is further fleshed out. Distinct types of intellectual capital

Figure 2: *An ideal model of HR analytics, integrating KDD (Fayyad et al., 1996), SDM (Mintzberg et al., 1976), SHRM (Lepak et al., 2006) and the subjective and universal perspective on data, information and knowledge (Zins, 2007).*



have been defined: human capital, social capital and organisational capital (Davenport, 2019; Nahapiet and Ghoshal, 1998; Schultz, 1961). These will be further described in the following sections, and allow for more detailed constructs of which the influence on HR analytics can be explored.

2.4.1 Human Capital

Human Capital is the most fluid form of intellectual capital, as this refers to the knowledge, skills and abilities utilised by individuals and cannot be directly retrieved from networks or organisational documentation (Subramaniam and Youndt, 2005; Schultz, 1961). The importance of Human Capital within HR analytics is expressed by Marler and Boudreau (2017) as the need for HR analytics practitioners, who have "right knowledge and skills to collect the correct data, perform the right statistical analyses and then to communicate the results in a meaningful and accessible way" (Marler and Boudreau, 2017). In a recent report, 51% of questioned organisations stated not to use HR analytics due to a lack of knowledge/expertise (Mulvey et al., 2016). In another report on analytics in HR and Finance, the response stated that the areas needed to develop or improve for HR were the growth of quantitative analysis and reasoning skills, and advising business leaders by telling a story with data and acting on data and analytics to solve issues (Davenport, 2019; Davenport and Anderson, 2019). Moreover, Rasmussen and Ulrich (2015) states that HR practitioners lack the skill and insight to ask the right questions about their data. In sum, the activities of HR analytics seem to be affected by the quality of human capital within an organisation.

Aside from HR analytics activities, the SDM routines are also affected by Human Capital. Mintzberg et al. (1976) stated that analysis mode during the Evaluation-choice routine during the selection phase of the SDM process was not often invoked and that the judgement mode was often chosen with disregard of analysis, due to time savings. This meant that choices were done without a formalising why a choice was made, essentially entirely by the knowledge of the individual making the choice. Whilst later SDM literature preferred the rational normative model, where analytical processes are more embedded in making strategic decisions, the importance of characteristics and knowledge of the decision-maker remained (Dean Jr and Sharfman, 1996; Hitt and Tyler, 1991; Hambrick and Mason, 1984; Mintzberg et al., 1976). Therefore, the Human Capital at the decision-making process also affects the way universal knowledge is utilised during the decision making routines and can influence the impact HR Analytics has on the strategic focus leading to improvements in the HR system. Moreover, this can affect the way the HR analytics process is triggered, as the threshold for the difference between expected performance and actual performance depends on the individuals that can trigger the recognition routine.

Thus, the construct of Human Capital seems to affect the way the HR analytics process and the SDM process are executed, and thus affects the way HR analytics enacts the characteristics of the SDM process.

2.4.2 Social Capital

Social Capital is as the knowledge embedded within, available through, and utilised by interactions among individuals and their networks of interrelationships (Nahapiet and Ghoshal, 1998). Whilst networks exist of individuals, the viability of social capital is not destroyed when an individual leaves the organisation, as is the case with human capital (Subramaniam and Youndt, 2005; Bourdieu, 1986). Social Capital is expressed in terms of norms for collaboration, interaction and the sharing of ideas (Putnam, 2000). The knowledge captured as Social Capital functions as a facilitator to strengthen how human and organisational capital is leveraged within organisations (Kostova and Roth, 2003).

For HR analytics, Social Capital influences any flow that requires the interaction between humans. Boudreau and Ramstad (2007) states the importance of a network of supportive stakeholders across the company hierarchy for the outcomes of HR analytics, as well as the accessibility of data. Here, accessibility is not only determined by technology, but also by the ability for people to make connections and communicate in the same language about the knowledge they have. Moreover, the interaction between stakeholders is also captured as Social Capital. This indicates that Social Capital affects both the SDM process as well as the HR analytics process.

2.4.3 Organisational Capital

Organisational capital is the institutionalised knowledge and codified experience residing within and utilised through databases, patents, manuals, structures, systems and processes (Youndt and Snell, 2004). Knowledge in the shape of organisational capital is quite rigid, both in its creation as well as in its utilisation; a set group of parameters and script is followed (Brown and Duguid, 1991).

In sum, organisational capital affects the way data, information and knowledge are captured and utilised by describing a set of institutional rules.

2.5 E-HRM

Marler and Boudreau (2017) suggests the capabilities of the e-HRM software to moderate the effect of HR analytics practices on HR analytics outcomes. Moreover, Angrave et al. (2016) argued that the tools and services used during the HR analytics process affect the state of HR analytics and that these tools should be selected with the strategic goals of HR analytics in mind.

In this section, the domain of e-HRM is used to investigate what aspects of e-HRM might affect the enactment of SDM-process characteristics by HR analytics. E-HRM can be as "a way of implementing HRM strategies, policies and practices in organisations through conscious and directed support of, and/or with full use of, web-technology based channels" (Ruel et al., 2007). E-HRM has been argued to exist in three types: operational e-HRM, relational e-HRM and transformational e-HRM (Ruel et al., 2007; Wright et al., 2001; Lepak and Snell, 1998).

Operational e-HRM focuses on the administrative area of HRM and aims to improve HR department efficiency (Bissola and Imperatori, 2014; Parry, 2011). Whilst HR analytics, in essence, tries to optimize strategic choices, operational benefits can emerge from the activities in the HR analytics process. Hannon et al. (1996) showed that the uniformity of data-enabled divisional and corporate reporting requirements. Buckley et al. (2004) found that implementing an automated screening and recruitment system did have operational consequences, yielding an ROI of $6.00 for every $1.00.

In both cases, one or more activities of the HR analytics process can aid the development of these operational types of e-HRM, for example by cleaning the universal datasets in order to perform analysis, the intermediary reports that result as information or automation tools using machine learning to make choices for people or advice people to taken an action, such as the automated screening and recruitment system. Here, the technology that facilitates operational e-HRM can either be created or enabled by the use of HR analytics or can aid the HR analytics process.

Transformational e-HRM aims to transform the HR function by improving its strategic orientation towards HRM (Shrivastava and Shaw, 2003). The transformational impact of e-HRM in empirical studies is mostly formulated in terms of time savings and available information to support an organisation in achieving its business strategy (Parry and Tyson, 2011). Ruël et al. (2004) states that transformational e-HRM involves activities that enable organisational change processes, strategic re-orientation, strategic competence management and strategic knowledge management. By providing support to a strategic decision-making process, HR analytics processes are activities that enable organisational change and strategic re-orientation, and thus should be enabled by systems aimed at transformational e-HRM. Here, the HR analytics process and the technologies used to extract information from large quantities of data can be seen as transformational e-HRM.

Last, *relational e-HRM* aims to manage and sustain the HR departments relationships with employees by improving HR services and directly empowering employees (Parry and Tyson, 2011). Relational outcomes of e-HRM are often related to how HR is perceived within the organisation, or how the organisation is perceived by existing or potential employees.

e-HRM has been shown to improve employee satisfaction (Panayotopoulou et al., 2007), change the way HRM programs are perceived (Reddick, 2009), affect employee attraction & retention (Beulen, 2009; Feldman and Klaas, 2002) and improve the employer brand (Allen et al., 2007; Panayotopoulou et al., 2007).

HR-analytics can aid the way employees make decisions. By providing insights to employees about their performance and combining this with the right practices such as performance-based compensation, the intention to act improved within employees (Aral et al., 2012).

Thus, HR analytics could fulfil a relational role throughout the organisation, by providing the right knowledge to employees to make decisions at any level.

In sum, the alignment of the technology and tools to the purpose of HR analytics plays an important role (Marler and Boudreau, 2017; Angrave et al., 2016). To evaluate this role, the various types of e-HRM can be used to explore the relationship between technology and HR analytics.

2.6 Institutional Isomorphism

Aside from factors affect the way knowledge is created within organisations and factors that affect the technical aspects of how this knowledge is derived from data, several external factors might also play a role in the HR analytics process.

Angrave et al. (2016) stated that the industry of HR analytics, in which various tools and technologies exist, induced *mimetic isomorphism* where one organisation imitates the others practices as it regards these as beneficial to the organisation, which occurs when an organisation is uncertain about existing practices (DiMaggio and Powell, 1983). This leads to the adoption of tools that might not even fit the strategic goals for which the tools are acquired, leading organisations to not blame the tools for not producing the right results, but the shifting strategic environment (Angrave et al., 2016).

Arguably, the other two types of institutional isomorphism described by DiMaggio and Powell (1983) can also affect the HR analytics process. *Coercive isomorphism* occurs when an organisation is pressured through formal and informal ways by external organisations, upon which the organisation depends, or by cultural expectations in the society in which the organisations reside (DiMaggio and Powell, 1983). An example of a formal way through which an external organisation is pressuring HR analytics practices to conform is the GDPR legislation, which made the use of personal data more restricted (Voigt and Von dem Bussche, 2017). This causes organisations to comply with the use of only certain types of data for specific use-cases, which could result in increase isomorphism of HR practices.

Normative isomorphism is related to professionalism, which is driven by the formal education of professionals in a certain domain, and by the network and growth of professionals in a certain domain (DiMaggio and Powell, 1983). Professions themselves are also prone to mimetic and coercive forces in this way, meaning that the skills and utilisation of these skills within individuals grows similar across a profession.

All these forces are problematic when viewed from the Resource-based view (Barney, 1991), as these forces limit the uniqueness of value attained by organisations through HR analytics. If everyone uses the same systems, processes and skills, no change or growth is expected in the field of HR analytics. Moreover, no unique value is created compared to competitors, as all use similar technology and techniques to perform HR analytics. Exploring how mimetic isomorphism affects HR analytics provides insight into how to avoid these pressures and develop unique value compared to the market through HR analytics.

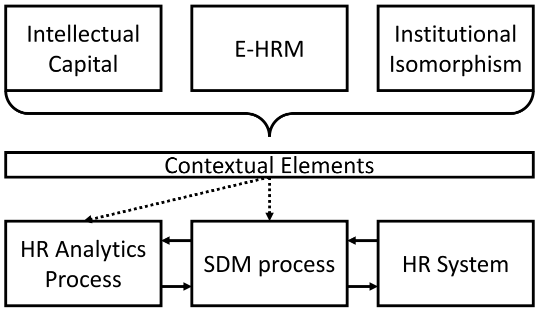
3 Methodology

To investigate the research question 'what characteristics of Strategic Decision Making are enacted by HR analytics', all constructs discussed in the literature review have been explored during a qualitative study using semi-structured interviews in the context of two case studies as a method of data collection. Moreover, a third case is introduced as Technical Action Research (TAR), where the researcher of this article was involved in the decision making process in which HR analytics occurred. The constructs and the relations under investigation have been visualised in figure 3.

In this section, the background of the cases, semi-structured interviews as a method, design of the semi-structured interviews, and the approach to analysing the interviews are described. Overall, the goal of the analysis of these cases was to discover:

1. What routines were performed throughout the SDM process, including the order.
2. How these routines were related to the HR system.
3. On which routines HR analytics enacted.
4. What HR analytics activities were performed, including the order.
5. How these HR analytics activities were performed.
6. How technology and tools were used during the HR analytics and SDM process
7. The role of individual ability, network and relationships and formalised processes and procedures during the HR analytics activities and SDM process
8. The role of institutional isomorphism during the HR analytics and SDM process.

Figure 3: *The relations under investigation during this explorative qualitative study.*



3.1 Background

This study was performed at a national Telecom Company. Within this study, the organisation will be referred to as 'TelCo'. TelCo is the result of a joint venture between two large global mothers. The TelCo is still in the process of becoming one organisation, bringing challenges to all fronts of the organisation, including the HR department. The merger was done by creating a 50/50 joint venture, making both companies shareholders in TelCo. In the context of HR analytics, several actors were deemed relevant a priori: the HR analytics practice (HRA) which emerged in TelCo around early 2017, and the Analytics (A) team, which performs analytics on general cases within the organisation, involving the HR, consumer and Business-to-Business domains.

Three cases were identified within TelCo in which analytics was utilised in the context of HR to make a strategic decision. Cases one and two were identified through a request from the manager of the HR analytics team and a senior employee of the HR analytics team. The request asked for a situation in which HR analytics was used to decide on the HR system. Case three was part of a Technical Action Research in which the researcher of this study was involved.

An overview of the people involved in the cases, and from whom the information will be extracted through semi-structured interviews or from experience in case of the TAR, is presented in table 1. This results in at least two interviews per case study, with a total of seven interviews for this case study involving five different people. As stated before, all these people played a major role during this project. Only a couple of individuals with minor roles were identified, such as roles on a 'to inform' basis, these were deemed too minor to gain additional insights in the scope of this research.

Table 1: *People involved in the case studies.*

Name	**Team**	**Function**	**Case(s)**
HRA1	HRA	HR analyst	1, 2
HRAM	HRA	Manager	1, 2
AA	AA	Analyst	2
AM	AA	Manager	2
AD	AA	Director	2
LMA	HRA	TAR	3

3.2 Method

The qualitative research method of semi-structured interviews brings along several advantages. Semi-structured interviews are a good way to perform exploration on attitudes, values, beliefs and motives (Barriball and While, 1994; Smith, 1975). Moreover, to investigate decision-making processes, Mintzberg et al. (1976) preferred interviews as 'the best trace of the completed process remains in the minds of those people who carried it out'.

Semi-structured interviews as a method fit the scope of this research, which is not the discovery of objective facts, but the subjective interpretation, such as feelings and experiences, of people of a case involving the HR analytics practice, to theorise about the relations presented in figure 3.

This study is case led, meaning that cases useful for this study to perform interviews about were identified a priori, as well as a set of actors relevant to this case. Additional relevant actors were identified during the interviews, resulting in additional interviewees identified after the first rounds of interviews, to properly capture the case at hand.

Enough actors are interviewed to gain an insight into what happened during the case according to the experience of the interviewees concerning the SDM process, HR analytics process and how contextual influences might have impacted these processes. During the interviews, the importance of interviewing other actors during the case studies emerged, who have been interviewed. Others mentioned in the interview did not alter the decision-making process in a way that has not been described by other interviewees and were thus deemed unnecessary to interview.

3.3 Design

To explore the way HR analytics enacts the SDM-process, semi-structured interviews were held with people involved in the decision-making process in which the HR analytics process played a role. Each participant was asked the same set of base questions, after which a semi-structured conversation would explore what happened during the case, to identify the enactment of HR analytics on the SDM process. These conversations occurred in an isolated setting from the other participant in a one-on-one conversation. First, to investigate the strategic decision-making process, a similar approach as Mintzberg et al. (1976) was used. The participants were asked to identify the strategic decision made during the case study and describe all intermediate steps that led to this decision. Guiding questions were asked to discover the steps taken during the SDM process, such as 'what triggered the begin of this decision?', 'where did management look for knowledge to guide the decisions?', 'What alternative solutions were present?. In short, a question existed to explore each SDM routine and the relation between these routines.

Whilst mapping out the SDM process with the participant, questions are asked with regards to each routine to see how HR analytics was involved, and what influence HR analytics had during these routines. Moreover, each participant was asked about the process of HR analytics similarly to the questions about the SDM process. The semi-structured approach emerges from the way the interview as conducted. An interview guide was used involving several questions about the SDM process, HR analytics process and the

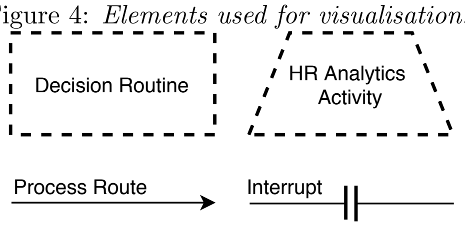
HR system, and an introduction of the interviewee and his/her case. Aside from the fact that the introduction would always precede any other question, the interview question did not hold any chronological order and was just there in the form of checkboxes to indicate if the question has been asked before or not. This gave structure to the interviews, allowing for consistent quality of the interview approach for each candidate, but also allowed for variation depending on the flow of the conversation.

Each participant was provided with a whiteboard and a screen to visualise or provide visuals for their ideas during the conversation. These visualisations were allowed as they could potentially aid the interviewee in providing chronological relations between elements of their potential unchronological story during the interview (Hove and Anda, 2005). Unfortunately, no visualisations were made, although presentations related to the cases were handed over by the interviewees to provide additional context. Using this research design, both the SDM process and the HR analytics processes are explored as well as the contextual elements that might have affected these processes. The results of the conversations were analysed by the research as described in section 3.4 'Analysis'. These results of the conversations were captured in a transcription of the audio files of the individual conversation. The drafted results compiled from the interviews were checked with the interviewees and corrected for any misinterpretations from the interview statements, such as wrong interpretations of the chronology of events.

3.4 Analysis

The transcription of the interviews were analysed using the models presented in figures 1 & 2. For each case, the routines, activities and contextual influences are extracted from the interview transcription. Using the elements in figure 4, the sequence of routines and activities is visualised. Only the activities, routines, interrupts and process routes are shown, meaning that intermediary data, information and knowledge states are excluded from the visualisation.

Figure 4: *Elements used for visualisation.*



4 Results

In this section, the results of several semi-structured interviews are presented by using the models presented in figure 1 and 2. The results are given for each case individually, after which a discussion section will relate the models to each other, as well as to existing literature. Each case is first summarised in a visual where all decision and activity routes are shown, as well as interrupts. This is followed by a thorough description of these events, where *decision routines* and *HR analytics activities* are deliberately emphasized. In addition to these events, based on the interviews, the reasons for taking certain routes are introduced. All of the results are presented with quotes from the interviews to show how each interviewees intentions. Furthermore, all names, countries, employee groups and numbers that do not add to the story are '<MASKED>'.

4.1 Defining HR Analytics

Before the case studies are presented, the alignment between the definition formulated in section 2.3.1 'Defining HR analytics' and the perception of HR analytics practice of the HRA team are evaluated. The HR analytics definition returns in parts in the several statements by HRAM and HRA1. First, the HR analytics practice agrees upon the existence of subjective data and objective data within the field of HR analytics, and that its the responsibility of the HR analyst to be able to measure these subjective data.

> I think the responsibility of the analytics team is reviewing the effectiveness of an intervention, looking if we are achieving what we wanted to achieve and measuring

> the necessary values. But not necessarily using KPIs, but really in values.
>
> *- HRAM*

Moreover, there is a clear difference between people data or 'HR-data' and business data. Here, HR-data seems to involve personal details such as gender and age, but also results of performance appraisals, engagement surveys or leave. Whilst individual performance indicators are available throughout the business, some types of HR-data, such as reward and engagement data, is inaccessible for analysis by parts of the business outside of the HR department.

> ... to improve the performance of mechanics when serving customers, we wanted to use not only the data from the business side, but also the HR-data, or at least we had the intention to add background information of the mechanics.
>
> *- HRA1*

The HR analytics practice views HR analytics as a way to inform the strategic decision-making process to improve decision making. Interestingly, HRAM desires to both inform the decision-makers or 'business' to arrive at new decision making processes or 'hypotheses' together with the HR analytics practice in addition to just informing on hypotheses already generated by the decision-makers. This means that deduction is already part of the HR analytics practice, and that induction is seen as part of the responsibility of the HR analytics practice, albeit that involvement of induction in the HR analytics process is not yet fully present.

> ...then you conclude that in certain domains you have X% of turnover, and you want to see the cause of this and cooperate with the business on 'what is this actually?'. And ideally, I want to do this with the business, they formulate the hypotheses and the analytics team checks these hypotheses. However, I want my HR analytics team to be a part of it, a spider in the web and a driving force.
>
> *- HRAM*

Finally, the HR analytics practice states that a goal of analytics is guiding their HR strategy by providing insights from data. However, this goal is formulated as an ambition, implying that currently, the strategic decision-making processes supported by HR analytics are not yet leading to changes in the HR system.

> ... where I want to be heading is that HR analytics will become a very important driver for the people strategy. ... this might be a bit too high of an expectation for now.
>
> *- HRAM*

Overall, the perception of HR analytics of this study and the HR analytics practice at TelCo is aligned on all aspects, albeit that some elements of the definitions are merely ambitions. This provides a reasonable argument to state that the case studies investigated at TelCo can be analysed with the concepts introduced in the literature section.

4.2 Case 1: Turnover Prediction

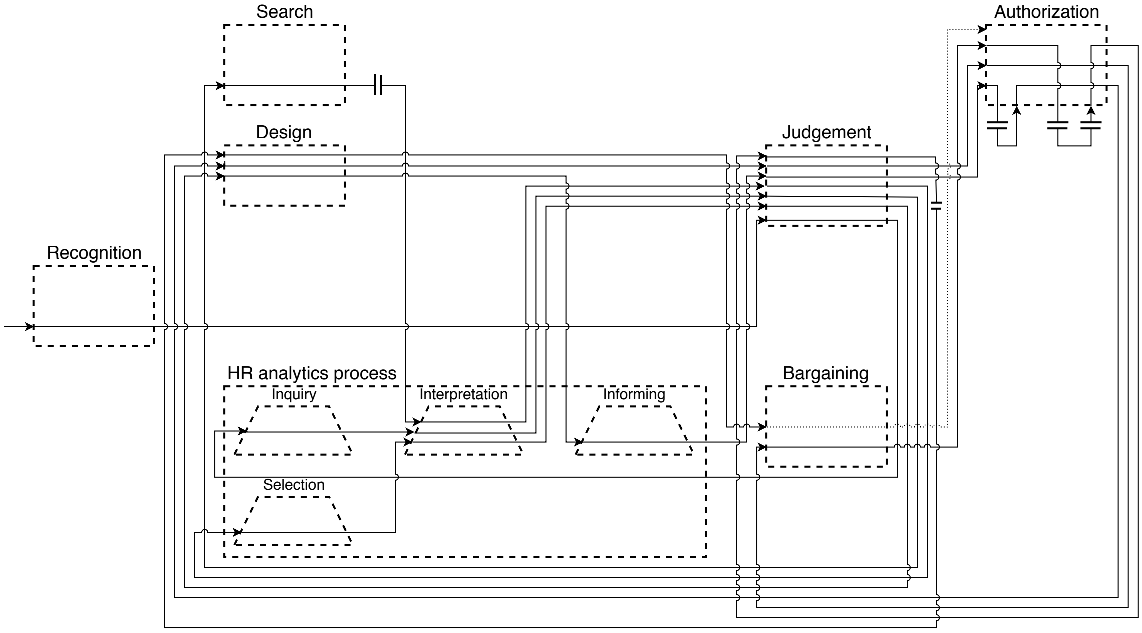
The goal of the SDM process in case 1 was finding an action, or intervention, that would reduce turnover within the organisation. The case can be summarized as a blocked modified search decision process for inductive HR analytics on interventions for employee turnover, where a pre-existing analytics 'template' already existed within the context of the organisation. The case is visualised in figure 5.

> *On confirming that the goal of the decision making process was reducing turnover:* Yes. At least identification of the riskfactors for turnover and based on these do targeted interventions.
>
> *- HRAM*

Normative isomorphism during recognition and judgement

This case was *recognized* by HRAM, who was inspired by a success case within Mother 1. Aside from the goal to reduce turnover, HRAM started this project because it was already successfully implemented at a subsidiary of Mother 1, and

Figure 5: *A blocked modified search decision process for inductive HR analytics with an existing analytics model template on interventions for employee turnover.*



could potentially show the value of HR analytics to TelCo. As this project was one of the first projects started by this HR analytics practice, the team still had to prove itself towards the business. After recognition, the HR director at the time[1] was informed of this case and *agreed* that a right course of action should be found regarding turnover, and that finding what type of action should be supported by HR analytics using the template of the success case within Mother 1.

> ... the other case *(case 1)* was inspired from a case implemented in <COUNTRY>, successfully implemented in <COUNTRY>, and of which we thought 'this would be a nice use case to show the value of analytics, not only for commercial goals but also employee goals ... that was the reason for jumping on this case.
>
> \- *HRAM*

[1] This is a different HR director then at time of writing

The HR analytics process started by an *inquiry* for knowledge on what action to take using the successful analytics template of the subsidiary of Mother 1. This template involved creating segmentations of employees based on turnover numbers and the general information available about these employees, such as age, education, amount of children, marital status etcetera.

This route is an example of the influence of *normative isomorphism*, where similar skills and techniques are used within a domain or profession, in this case within the context of the global partners of TelCo. This phenomenon impacted the recognition routine and decision route afterwards in two ways. First, the proof that the existing template would result in useful information to make strategic decisions on a lowered threshold for choosing to use HR analytics to find interventions to lower turnover. Second, no search process was invoked by HRAM as an existing solution was already present. This resulted in a data analysis inquiry where a template approach was already presented to the HR analytics practice.

Lacking organisational capital and technology causing a search interrupt
HRA1 executed the HR analytics process. HRA1 started by *interpreting* the inquiry in the context of readily available data and *decided* that it was necessary to *search* for the required data to decide if enough data was available. This search resulted in several datasets useful to execute analytics based on the template. Access to the data was not always straightforward, as data was spread across various systems. This resulted in an interrupt after the required data sources were identified and an interpretation could be made on how to progress.

> .. an important factor was the fact that the basics were not really in place. Maybe it's better now, but we had two, actually a lot of different systems. Maybe even ten. We had no common data definitions, data was not in one location but maybe five or ten systems. So to collect all the data... And data quality is a disaster, and back then was even more of a disaster.
>
> \- *HRAM*

An *interrupt* occurred due to two reasons. First, finding that the data existed was not the issue, as people within HR were already working with various types of data. Finding where the data was stored became an issue however, due to the HR department working in various systems. This is attributed as a technology issue, where having access to the data from one system would resolve this interrupt partly.

Second, a lack of formalised data definitions and formal processes to store HR data resulted in a search for these definitions at various people within the organisation responsible for the data, causing an extension of the search process. This is attributed as an organisational capital issue; having formal procedures for defining data and maintaining data quality would prevent having to search the organisation for definitions.

> One thing I checked, does someone has children or not, can I access that data. Conclusion, those are not in the personnel system, but in retirement system.
>
> \- *HRA1*

Individual knowledge and experience causing a modified design
Interpretating the available data, HRA1 made the decision to perform a *selection* activity, where the variables and constructs were selected to base the knowledge discovery process on. *Interpreting* the selected variables, HRA1 chose to alter the successful analytics template of the subsidiary of Mother 1. This choice to several *design* decisions that modified this template.

First, HRA1 was looking for a set of employees that performed a similar job, making it easier to make claims based on analytics of the population; the number of exceptions to the rule would be limited.

> We said <POPULATION>, because there the most similar job was being done across people. It's very hard to compare the whole organisation between <POPULATIONS>, so we looked for a homogeneous group...
>
> \- *HRA1*

A population was selected fitting the homogeneous criterium and for which quite a lot of data was available in terms of support and variables. In the understanding of HRA1, choosing this population would provide the benefits of a homogeneous group for analysis, and moreover, allow for more interesting analytical models due to the number of variables in the data available for these employees.

> We knew turnover is high. Then you ask 'where is it', it is in the <POPULATION>. And surprisingly, this is a homogeneous group, but also big. We had a lot of measurements. ... The logic to look there was present. There was no incentive, after we would be done, to have a spin-off to the rest of the organisation.
>
> \- *HRA1*

Based on the additional data for this population and prior experience with lacklustre results of analytical models similar to the template, HRA1 modified the original template in two more ways. One, Absence and leave data were added as a variable and two, individual psychometrics were added, which were collected during the recruitment of the target population. The individual psychometrics made the selected employee population stand out, as these psychometrics were not collected for other employee populations.

> *When asked about using the existing approach of the success case:* I knew nothing useful would come out of it. They have tried it hundreds of times, there is no real article about it working, I'm quite realistic in that sense. The gain was in trying to do more. ... I've also tried them 10-20 years ago but it never returned much. The gist was in the early prediction based on leave and psychometrics.
>
> - *HRA1*

The first added variables, absence and leave, were added due to their predictive value for turnover. HRA1 had experience with this model from past working experience, and moreover, found evidence in the sociological and psychological literature that these two variables had predictive value with regards to turnover, described as 'physical withdrawal'.

> We wanted that early warning, well there are nice psychological and sociological models that tell you to look at who a person is. And if there is any physical withdrawal ... I mean if you want to leave you need to have interviews somewhere. This can impact leave, but there are a lot of articles that state that people would call in sick. So we had the luminous idea to add absence and leave as an explanatory variable. ... These are models with which I have experience from my past. It allows you to estimate, using segmentation, where you run more or fewer risks.
>
> - *HRA1*

The second added variables, the psychometrics, allowed for more sophisticated segmentation and would allow for the ability to give an early warning about an individual employee. This would allow interventions on an individual level.

The choice to modify the existing design can be attributed to the domain-specific experience and knowledge of HRA1 on the topic of turnover prediction. Someone without this experience might not have doubted the initial template and followed its design without any modification. This emerges mostly during the interpretation of selected data after a choice is made to alter the design. At these points, personal knowledge was applied to information derived from data.

This shows the importance of human capital during the activity of interpretation; a regular analyst would be able to select data for to achieve a homogeneous group, but the importance of certain variables for predictions emerge from knowledge and experience in the HR domain. This indicates that human capital can alter the interpretation of information and subsequent judgement on the right course of action and eventually, the way HR analytics outcomes are developed.

Misinterpreting the implications of a modified design

The modified design entered an *informing* activity by HRA1 to HRAM, leading to a *judgement* by HRAM on the findings of HRA1.

Here, the implication of the informing activity arises, as HRA1 gained subjective knowledge from interpreting data and extracting information. HRA1 had to transfer this subjective knowledge to universal knowledge understandable by HRAM. In an earlier quote, HRA1 states that the was no intention to increase the scope of the project to other populations, after selecting a target population. HRAM, however, did not perceive this. These type of misinterpretations can result in a differing expectation about the outcome of the decision-making process between the HR analytics practice and the stakeholders depending on the HR analytics outcomes.

> *On if the reduction in turnover was general or targeted at a specific group:* ... At first instance general, so we looked at the entire population at TelCo. We thought let's formulate the hypothesis that turnover is generic, if you can distil a few of these

> generic elements, we can see what we can achieve with the available data
>
> *- HRAM*

Coercive isomorphism through block caused by conservative approach
Before the extraction of knowledge could be done using the adapted design, an *authorisation* routine was initiated with the privacy office. This was done to check if there were any implications of the recently implemented General Data Protection Regulation (GDPR) within the EU. This authorisation was seen as a long process, as the privacy office remained inconclusive for a long period. At some point, HRA1 decided to explain the privacy office repeatedly what type of analyses was done, what techniques would be used, to receive a response. After this *interrupt*, the modified design was not authorised.

> ... it did take quite a while until the privacy office opened up. They felt quite uncomfortable that we were showing up with HR data. 'Who is going to do that and where?' This was the phase where I had to explain the privacy office what open source software was.
>
> *- HRA1*

The variables leave and absence was not allowed to be used, as it was determined a sensitive data object, even with measures to anonymise the data, as the amount of individual data used was determined as enough to sequence it back to an individual. This came as a surprise to HRA1, who was not aware of how strict this ruling was.

> ... that was also a learning, the absence is not allowed. What made this surprise even worse was that not only absence but also holiday or leave data were not allowed. Neither was the combination. ... it was more strict than I expected.
>
> *- HRA1*

Psychometrics could be used but required that the psychometrics were collected with consent through an opt-in option. The use of this opt-in was considered but would require radical changes to the existing processes, such as explicitly asking for the consent of the potential new hire to use that acquired information to analyse voluntary leave of the organisation.

> I had to do a bunch of things, such as getting proper access to psychometrics data, acquire it with a different disclaimer, a different reason for collection etcetera, so I would have disrupted a lot.
>
> *- HRA1*

The authorisation route in this decision process was a careful choice, an attempt to explore the implications of the GDPR; a more aggressive approach could have resulted in a bypass of the privacy office by just requesting the data and seeing what would happen, and performing the analysis anyway. HRA1 responded to the uncertainty of the GDPR by finding certainty through compliance. As a consequence, *coercive isomorphism* occurred, where HRA1 was forced not to use certain types of data and statistical models in the HR analytics process due to external legislative forces.

Political redesign as a workaround
In response to the denied authorisation, HRA1 made a political *design* choice, to circumvent the denied authorisation. HRA1 at the time was in contact with a DPO[2] of Mother 1, since the original template came from their hand, and discovered that the modified design could be implemented at Mother 1. At the same time, the design choice was made to exclude the psychometrics from the modified design, as using psychometrics for turnover prediction would require changes to important HR practices. The existing recruitment would be impacted, as each potential hire would have to be asked for explicit consent to use their psychometrics for turnover prediction. Thus psychometrics would be held-off until some initial results could be presented using the modified model with absence and leave.

> The fascinating thing was that at Mother 1 in <COUNTRY>, they stated that their DPOs would allow it. ... For a part, you can use the data, as long as you properly

[2]Data Privacy Officer

> anonymise it, such that you cannot trace it toward the individuals...
>
> *- HRA1*

Besides, Mother 1 had already done achieved some successes with HR analytics, for example with the initial analytics template. This gave HRA1 the belief that they were capable of executing the analysis as intended, and more importantly, it allowed HRA1 to discover what was required to request a mother organisation to process data abroad.

> Why did I do it, because of the GDPR. I wanted to see what the implications would be of using your own mother firm. In other words, our mother is shareholder of TelCo; to what extent is TelCo data Mother 1 data?
>
> *- HRA1*

HRA1 wanted to test this due to the complicated situation of the merger of TelCo, which was a consequence of a 50/50 merger between Mother 1 and Mother 2, who are competitors on a global scale. Sharing information between the Dutch subsidiary TelCo and the mothers had been under scrutiny due to the competitive relationship between these shareholders, giving HRA1 a case to test the waters in terms of sharing HR analytics data. Choosing this route would not only result in the ability to execute the case but would also allow the HR analytics practice of TelCo to access external capabilities when internal capacity was too limited to perform analysis within TelCo.

> We wanted to see what the implications were of doing data science this way and if it is possible because one of the ideas was that if you have a limit in data scientists like me, you can always find one somewhere else.
>
> *- HRA1*

Here uncertainty about the implications with regards to the GDPR would lead to HRA1 wanting to experiment with Mother 1 as a data processor. Moreover, the international network of HRA1 would allow HRA1 to do such an experiment.

Second block and shifting priorities

This political redesign was *agreed* upon by HRAM, and required two authorisation processes, one from security and one by the privacy office. The *security authorisation* resulted in negative advice, after which a *bargaining* between security and HRA1 resulted in a checklist on what data transfer security to comply to transfer data from TelCo to Mother 1. This resulted in a second *authorisation* routine, which was first interrupted when consent was required by the shareholders Mother 1, Mother 2 and TelCo to have Mother 1 as a third party data processor.

> ... pumping data to Mother 1 was a big hassle. There was a consent form that went from one to another that eventually got signed. So we could solve the issue, but it was a long process.
>
> *- HRAM*

The privacy office of TelCo was also involved and caused another interrupt. Again, the implications of the case had to be fully understood, causing the privacy office to wait long with the authorisation decision. The potential benefits had to be properly weighed against the legal implications. Again, the privacy office stated that the leave and absence data could not be used. This resulted in a judgement by HRAM and HRA1 to discontinue the project for now.

Whilst HRA1 had some ideas to continue the project, shifting priorities led to a long *interrupt*, as the choice was made to put the project on hold. The HR analytics team was not only responsible for HR analytics, but also in part for Organisational Design, and thus played a big role in the reorganisation of TelCo after the merger. Acquiring insights into possible interventions in turnover using HR analytics had taken quite some resources away from this reorganisations, and priorities started to shift. The project 'bled-out', as no progress was made due to these shifted priorities.

> Not unimportant, at the time we were actively integrating, meaning a lot of reorganisation happened... I think the timing just wasn't good.
>
> *- HRAM*

Redesign, bargain, comply

Nearly a year later, HRA1 has overcome the *interrupt* caused by shifted priorities due to several developments[3].

First, the reorganisation process is coming to a close, giving more time to the team to spend on HR analytics as opposed to organisational design. Second, the privacy office has matured and is now actively talking about mitigation for potential privacy issues opposed to completely declining a request. Third, more data became available for analysis that would allow for a redesign of the analytical model, a result of a search process related to case 2.

HRA1 has started a *redesign* of the way the analytics would be presented; instead of doing analytics and coming to suggested interventions on an individual level, the analytics would be presented through dashboarding. In this way, individual interventions would not be possible anymore, but the analytics could still be visualised and used to adapt the HR strategy with general interventions for the target population.

Based on this design choice, HRA1 is now actively discussing with the privacy office to comply with the GDPR and proactively inform the privacy office on the design. This *bargaining* route was not yet taken earlier in the decision process, as the privacy office was at the time not actively discussing cases, merely authorising. Now, however, the privacy office has matured in experience and capacity, allowing for active discussion.

> I've now, in a different way, more through the dashboarding way, applied again, and we are again in a dialogue with the privacy office... right now, we have a new DPO who says listen, I understand you, but you cannot do this, but I want to think with you under which conditions you can do certain things securely and orderly. A completely different atmosphere, we currently have.
>
> \- *HRA1*

This active discussion is the consequence of social capital within the organisation. Whilst HR and the security department where not new within the organisation due to existing relations from HR technology implementations, relations between the privacy office and HR still had to be established. This can be derived from the explorative stance HRA1 had whilst delving into this project. It was the first interaction with the privacy office, and HRA1 wanted to explore what the privacy office would do. This resulted in an improvement in the social network between HR and the privacy office, of which HRA1 is now reaping results.

In sum, no HR analytics outcomes have been derived from this HR analytics process thus far. Acquiring the data was difficult, as it existed in various systems and lacked in data quality. After data was collected, a choice was made to redesign the template solution which, according to HRA1, would not have yielded results otherwise. This redesign caused a block by the privacy office, who was on edge due to the GDPR legislation. Whilst a political redesign occurred to circumvent this, the privacy office remained adamant on not doing the analysis. Due to a change in priority, the HR analytics process was put on hold. Recently, more time came available for HR analytics projects, allowing the continuation of the HR analytics process. Through a redesign, HRA1 attempts to continue to provide insights into the original SDM process to decide on interventions to lower turnover. Moreover, HRA1 has entered an active conversation with the privacy office by bargaining over the design choice before the authorization request.

[3] This sequence of events is occurring at the time of writing

4.3 Case 2: Smart Task assignment for Mechanics

The goal of the SDM process in case 2 was finding a way, using HR data and business data, to better match mechanics with tasks, such as technical problems at the client. In this case, better was evaluated based on the KPI 'First time Fix' (FtF), which interviewees defined as ‘if a mechanic does not have to return for the same problem within 24-28[4] days’. The case is visualised in figure 6. Here, a design routine is seen as a part of the HR analytics process, as all HR analytics activities embedded in the design routine involved iterative design decisions.

Approaching an issue with the wrong hypothesis

The *recognition* of this case occurred between the Director Installation & Maintainance (DI&M) and HRAM, who met each other at the coffee machine, where D&IM explained that they were working on improving the operations of the Installation and Maintainance (I&M) department using mechanic data. In response, HRAM talked about the HR analytics practice, and how they could do a joint project with HR data. Together with the HR director[5] at the time, a *choice* was made to see how HR data could be used to improve the operations of I&M, specifically using available data on mechanics and their tasks, including HR data.

> ... we decided to meet, we met and that is where the mechanic case came from. ...It all happened very informally, they also wanted to do something with employee data.
>
> \- *HRAM*

HRA1 was told about the case by the HR Business Partner (HRBP) for Customer Operations, under which the department of I&M falls. HRBP introduced HRA1 to DI&M, presenting several Key Performance Indicators (KPIs) on which an improvement could be made, of which FtF was deemed the most important. At this point, HRA1 made the hypothesis that FtF could be improved using available employee data and task data provided by the business and HR.

In retrospect, HRA1 stated that this was a wrong hypothesis, as the FtF was already quite high, making for a weak business case. Early identification of an already high KPI might have led to a different evaluation of the business case for the use of HR analytics, a different expected HR analytics outcome and thus a different progression of the decision-making process.

> ... nobody put us on the right track, or we were unable to formulate the right question, that was the issue, the right hypothesis, that on the first time fix the definition of three months, that there was an actual gap.
>
> \- *HRA1*

Bargaining with the different priorities between HR Analytics Team and Analytics Team

AD got involved by HRA1, as AD was identified as an essential partner. Most company data was available for analysis on the Analytics Platform, which was used by the AA department, responsible for analytics throughout the business, of which AD was the director. This resulted in a *bargaining* process between AD, AM, DI&M, HRA1 and HRAM.

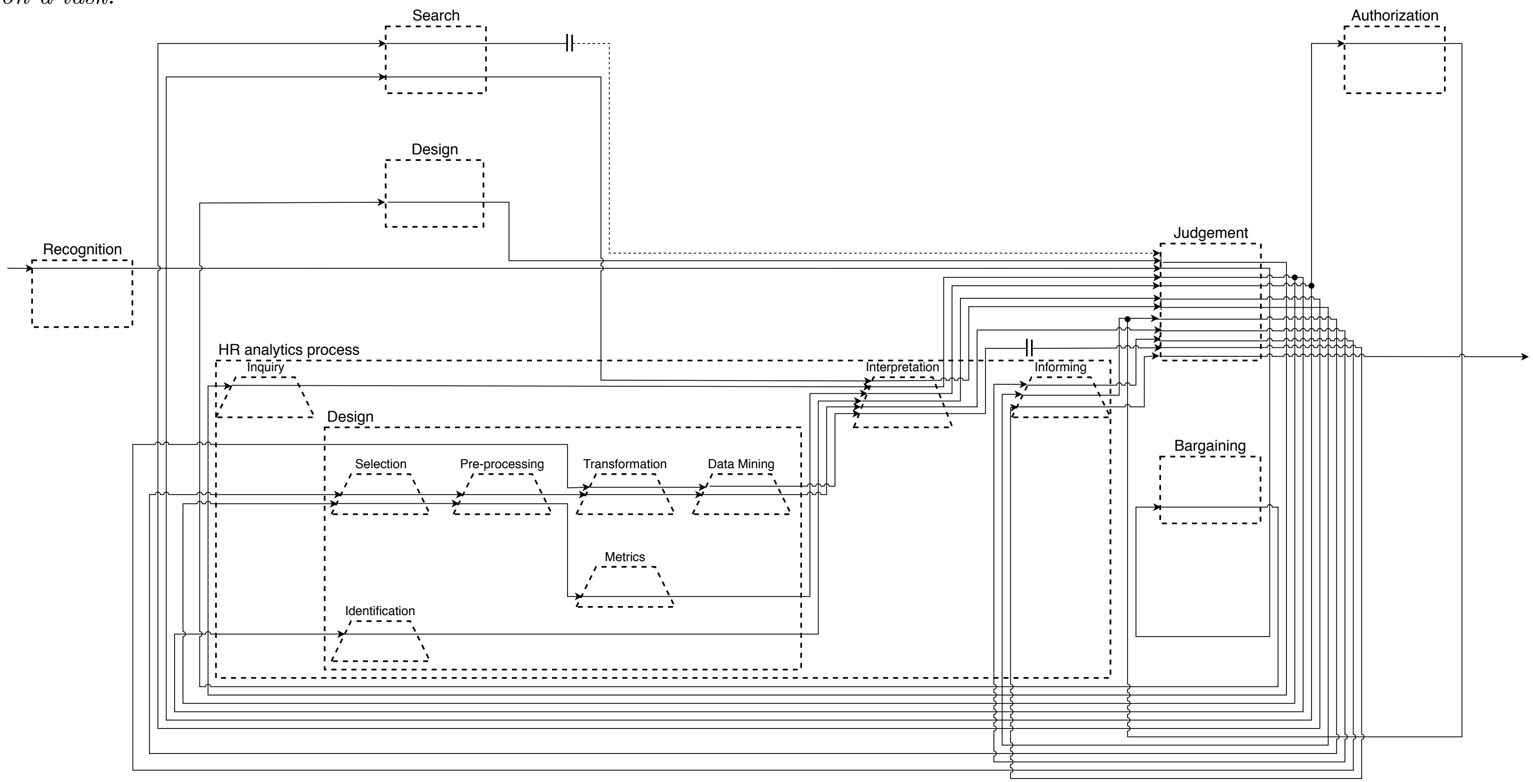
Whilst the bargaining routine did not involve contrasting opinions about the decision at hand, the analytics team and HR analytics practice had different priorities regarding the outcomes of the whole decision-making process.

> Looking at mechanics is interesting, as we can generate a lot of impact in terms of money, but also customer experience. That was the intention of the Analytics team. For HR the intention was also the ability to coach... being able to steer the mechanic on performance and growth.
>
> \- *AM*

[4] interviewees defined FtF with numbers in the range of 24 to 28 days

[5] This was the same HR director as in case 1

Figure 6: *A design decision process with a parallel search process for a statistical model to predict how much time a mechanic spends on a task.*



The bargaining routine concluded, after which several political *design* choices were made to perform the project AD acquired an external data scientist, AA, who would work with the resources of the Analytics department under the supervision of HRA1, and with the coaching of AM. Moreover, HRA1 came with a budget to fund the project, easing the final *choice* to start the HR analytics process. The decision making would continue with the development of a statistical model that could predict the time a mechanic would spend on a case, and see if this results in a first-time fix.

> What certainly eased the whole process was HR making budget available. Then you move from something large to something more concrete. ... Can we predict how long a mechanic will take on a case, and if that is a good fix.
>
> \- *AM*

Here we see an example where part of the HR analytics practice is 'outsourced' to another department. In the HR analytics process, HRA1 was mostly involved in identifying and finding useful HR data, whereas AM would support AA in finding definitions for analysis and interpreting the data. Moreover, the Analytics department had different intentions compared to the HR analytics practice. Where the Analytics department wanted to make an impact financially, HR had the ambition to also improve learning and development. This serves as an explanation for the focus on operational value creation during the HR analytics process, with the KPIs as the main guideline, opposed to the creation of strategic insights for HR, for example improving the learning and development of mechanics.

The importance of the social network in search and knowledge of organisational processes in authorization

Whilst AA was being onboard, an *inquiry* for two assignments were given. One assignment involved discovering an optimisation resulting in the optimal mechanic for a specific task. Here, the focus of the assignment was on creating operational value by increasing FtF.

> AD told me, that was some type of intake for me, 'we have an HR case, for which we can use your knowledge. We have a large group of mechanics and an X amount of cases, which have been classified, how can we match these?'
>
> \- *AA*

As a secondary assignment AA and HRA1 were *inquired* to discover where any missing HR data regarding mechanics could be, as HR data was not readily available. The only available HR Data were the mechanics KPIs. All available data existed on the Analytics Platform (AP), a platform owned by the AA team. Here, the focus of the assignment was on creating strategic value by identifying missing HR data and gaining insights on how to improve the HR analytics practice.

> ... not everything about the mechanics was available on AP, so that was sort of a secondary assignment. Find out where the data is, try to acquire it with the help of HRA1. ... AD gave me access to AP, I still had to add the HR data.
>
> \- *AA*

This led to three different decision routes. As part of the first routine, based on the data that was available on AP, AA started to *interpret*, and *judged* that quite some data was available for an initial analysis. With the available information, AA began *selection* and *pre-processing* of existing data, where during the *extraction of metrics and descriptive statistics* and *interpretation* of the results, questions arose about unknown data types, formats and outliers. AA *judged* that more context was needed and *searched* the organisation to find people that knew satisfying definitions and clarifications for the anomaly data.

Here, an element from the model in figure 2 is adapted, the HR metrics activity. As this activity is not limited to purely HR-related metrics, this activity is described as *metrics*, wherefrom preprocessed data, one extracts information in terms of metrics and descriptive statistics to discover the meaning of individual elements of data and their content, opposed to the larger patterns that they should represent.

> I was told this is the use case, this is what we wanted to do, we have available data and we still want to add data. So you know data is there, so you start asking: how can I identify mechanics, can I get logical metrics such as how much are they deployed, how many cases do they get on a day, how can I fact check this data that if what they are using now is valid.
>
> *- AA*

AM had a supportive role, helping AA with the right network to find information regarding the data to help the interpretation activity. Moreover, AM made sure the project was safe with regards to legislation.

The latter caused a second route towards an *authorisation*, necessary if AA wanted to develop a statistical model. This authorisation happened after the interpretation of the exploration activity, which resulted in draft *design* for the data that could be used to develop a statistical model. To proceed with the development of this statistical model, an authorisation was required from the privacy team, as dictated by a formalised process on data compliance within the organisation.

> We have a platform with a lot of data, well I helped AA by pointing into the direction of people that could provide good knowledge about the data. And the part privacy/legal, so arranging that the case was within the range of the GDPR, legislation and reputation impact.
>
> *- AM*

This shows the importance of social capital to properly understand organisational data, as, without AM, AA would have been clueless on whom to approach to properly interpret the available data. Moreover, the knowledge of AM about the potential legal implications helped to ensure the outcomes of the HR analytics process were safe in terms of legislation. Finally, AM had proper knowledge of the procedure of acquiring approval for the project from the privacy team, knowing what was covered by existing approvals and what elements would require re-approval, something HRA1 in case 1 was unaware of.

Identifying and searching for existing HR data

The third route revolved around missing HR data on AP. HRA1 and AA, based on the previous interpretation of the available HR data on AP, *identified* missing data that could support the statistical model. To find this missing data, AA and HRA1 started a *search* for HR data, as it was assumed that the identified data that could help the model was already available within the organisation. This was described as a routine where 1) existing HR data was localised and 2) the effort requiring the extraction of the HR data was estimated.

For step 1, an identification activity is present but with a disconnect with a quantification activity, as HRA1 *judged* that the universal form of some subjective data must be somewhere within the organisation already. Access through the AP platform or other ways has not been formalised for this HR data. The choice by HRA1 to not quantify new HR data is attributed to the fact that already enough new HR data could be acquired from the social network of HRA1, and the knowledge that some universal data could already represent subjective data about people. For example, a difference in contract type could capture a difference in both expertise and job culture.

For step 2, the effort requiring the extraction of HR data had to be collected to weight against the added benefit of adding this data to the predictive model. Whilst one can add data to a statistical model to improve results, at some point the saved effort after improving the model does not outweigh the required effort to improve the model by acquiring new data.

> You can also say, as soon as I have this data, how good am I then. If I add more how far will we get? If I keep adding I might be able to predict everything, ... How far can you get with the data you have.
>
> *- AA*

Implications of wrong hypothesis and emerging implementation issues

Whilst the search for HR data was still ongoing, AA already concluded the search for correct definitions and explanations for anomalies, found these explanations and assumptions *acceptable* and started *interpreting* the initial data. Then it was found that the main KPI to optimize, FtF, was already quite high.

> We saw immediately that the first time fix was not that bad. A small miracle had to happen if we wanted to improve that. What we said is that we would continue the project to explore if maybe there was missing data. We did an explorative conclusion that nothing might result from the project and that there were some risks to the implementation.
>
> - *HRA1*

This interpretation was possible due to the search initiated after interpreting the exploration activity. The search exposed AA to the business logic behind certain data with the help of the social networks within the organisation of AM and HRA1.

> You just get a bunch of tables, with visits of the mechanics ... I asked what would make a good mechanic, 'well, if they are in service for about 10 months', then you can start generating features based on this logic. But also to make sense of what is in that table, of the features. Most of the time these are codes with business logic behind them, like 'all tasks with code AE are difficult'.
>
> - *AA*

Moreover, awareness started to grow about the implementation of the case, since finding the data definitions involved talking with the product owners of the existing IT solution that made the existing task distribution over mechanics.

> The HR data never came, but when we started to search, HRA1 also made some progress. 'You have to talk to him and him', so I went talking or calling. ...Then you discover that they were already doing projects... and these were the people that we needed to implement, the end-users and business owners.
>
> - *AA*

The implications of implementing the solution emerged. To impact the way mechanics would be assigned to the task, the IT solution responsible for the task division among mechanics had to change to use the outcome of the HR analytics process. In the meantime, the product owners were already busy with improving the IT product in a similar way. Three issues emerged from the interview. First, the product owners had no time to aid in the implementation of the HR analytics solution in the near future and second, the changes to the planning done by the product owners would prevent measurement of the impact of an implemented HR analytics solution. Third, not only changes to the system but also changes related to the merger TelCo was going through led to various issues with measuring the impact of the HR analytics outcome.

> If you try to do this top-down, without it resonating across the business, or without the rest of the business being aware what is bound to happen, it is by default doomed to fail. This was a classic example of that.
>
> - *AA*

> One was how you would serve the end-product to the mechanics, the second was how you would measure these results. Especially at the start, you could be temporarily worse off with such a model, how will you measure this. This resulted in various challenges. First was the system that assigned tasks to mechanics ... that system had a whole upgrade scenario which was fully booked for the coming three quartiles. You could look at a workaround, but how will you measure the results.... at the time, mechanics were changing teams, teams started working differently, there was no like-for-like comparison between before and after...
>
> - *AM*

Continuing on the same hypothesis to get first results

With the search for HR data and the effort to extract this data continuing, an initial *interpretation* was already made by AA, leading to the *choice* of AA that it was time to *inform* AD, HRA1 and AM, leading to a *judgement* by AD, HRA1 and AM. Even though the KPI was already quite high resulting in a weaker business case, the project was not yet over, all wanted to run the models to see if something could come out of it, even though AA thought not much would come from it.

> The first iteration you do if you have the data, so is the data there, can you say something about the end goals. Can you solve the problem? With that data, we wanted to achieve a recommender model as fast as possible, that was the second phase.
>
> *- AD*

Besides, they might find a reason to acquire HR data to strengthen the analysis; from the perspective of the HR analytics practice, it was interesting to find a potential 'gap' in the HR data that could benefit future HR analytics cases.

> At the time, we said that we wanted to go through with the project, as we wanted to discover if there was a deficit, a gap in the data. ... if it appears that the data was too thin to do anything, maybe you would require another type of data, we wanted to test and know this. Then it would get really exciting, as we could use human data that we weren't using at the time, such as engagement.
>
> *- HRA1*

It was decided to develop a statistical model. The data usage was authorized before this judgement routine, allowing AA to immediately start *designing* the statistical model.

The project continued, where based on the judgement and the knowledge about anomalies and definitions in the data, *selection*, *preprocessing* and *transformation* activities were done. During all these activities, various *design* decisions were made. Each activity in this HR analytics process itself was an iterative process, including data mining, where small design choices were made to achieve the desired HR analytics outcome as defined during the inquiry.

> *In response to the lack of data quality:* Yes, you can't do anything with that, you could always say 'at that time, they updated the definitions'. For example if the definitions have been updated 9 months ago, you just cut-off all data before that time, creating a new dataset.
>
> *- AA*

On these transformations, a *statistical model was built*. This model could predict with a 28.7-minute error how much time a mechanic would spend on a case. Whilst this would help assign cases in a better way to mechanics, the relation between this and FtF was assumed. Based on this model, statistics were also calculated on what the impact of using this method to send the mechanic that would spend the least amount of time on the case would be on the FtF, and to no surprise, the impact on FtF was not that high.

Implications of data quality and implementation issues

Interpreting these results gave AA reason for various concerns. Whilst *informing* AM, AD and HRA1 in several one-on-one conversations, the *judgement* after this informing remained to continue. After one more iteration of *transformation* and *data mining*, slight improvements showed in the models predictive ability. After *interpreting* this second iteration, AA *decided* to *inform* the stakeholders about various concerns with a negative advice to continue. At the time, AA was still searching for explanations and ways to see if the implementation of the HR analytics outcome would be feasible. However, acquiring all the necessary information to properly interpret everything took quite some time, causing an interrupt in the interpretation activity before the judgement to information could be made.

> When we arrived at the implementation part, all the meetings came ... All these meetings could have been done in two days, but before everything was done. That took quite a while, whilst in the meantime, not much progress could be

> made on the project.
>
> - *AA*

First, some data quality issues, such as external mechanics being written as one in the dataset, did not allow for reliable modelling, as these mechanics would appear as one very productive mechanics in the data. Whilst most interviewees say that these could be overcome, the consequences might be a model that shows good results on the cleaned data without applying to reality. Moreover, the impact of the existing modelling was already not that significant against an already high KPI.

> You can not predict from a context that will not happen, you can't predict that a mechanic should go when that mechanic is an assembly of thirty mechanics. It doesn't work like that; a mechanic isn't thirty people
>
> - *AA*

Second, concerns existed about the actual product owners of the system in which the HR analytics results would be implemented were already busy with implementing their changes. This left the HR analytics outcomes without support or ownership to be implemented in the system that would serve tasks to mechanics.

> As long as the roadmaps are not aligned, as long as we are not working on the same outcomes but against each other, it actually made no sense to do the case.
>
> - *AA*

Third, various changes to the organisation of mechanics as well as changes to the task assignment tool made it difficult to assess the impact of the HR analytics outcomes after implementation.

Freeze due to shifting priorities

Based on this information, the choice was made that the project would remain on hold based on the KPI of FtF and the difficulties in implementation. After that, AA left the organisation as an external analyst. This did not mean that the decision-making process ended; a long *interrupt* occurred due to lack of business interest in further developing the case, but the case remained available for reopening. Moreover, the search regarding localising and determining the effort required for acquiring additional HR data never concluded in a judgement.

AD gave negative advice to continue, as the business case was not large enough.

> At that moment, it was a low impact case, ... , we were searching for other things where we had a different impact.
>
> - *AD*

HRA1 however still wants to see if the project has a reasonable business case if the definition of the KPI, which is based on 25 days, is changed to something different, as the definition was quite ambiguous. Moreover, since the HR data search never stopped, as HRA1 was working on this in addition to AA, new data such as engagement data and reward data might be available in the near future, as indicated in case 1. This means that whilst *interrupted* the second search routine might still result in a decision to acquire more HR data to enrich the model if the project is restarted.

> The project stopped because of a budget issue ... we went back and said, if we make a better impact, put the hypothesis correctly on that first time fix of three months, we can see what we can do.
>
> - *HRA1*

HRAM states the core reason for the project being on hold is the inability to get past the process owners approval. Also, same is the last case, HRAM states that the timing just wasn't right, causing a lack of business support due to shifting priorities and budget issues.

> At the time, we were quite an hierarchical organisation, making it difficult to achieve something without the explicit approval from the top.
>
> - *HRAM*

Whilst several valid reasons of concerns were given to stop the project, in the end, the choice of AD to discontinue the HR analytics process based on the low impact and the choice of AA to leave the organisation at the time was the main driver behind the freeze of the HR analytics project and the resulting lack of HR analytics outcomes.

4.4 Case 3: Question Answering System for HR tickets

This case is described from the researcher's point of view, who performed technical action research on the design of a question-answer system that could answer an incoming question from employees by e-mail in an automated way. The HR analytics outcome was a statistical model that could classify a subset of employee questions. The goal of the SDM process was the selection of a solution that would reduce the workload of HR employees. The case is visualised in figure 7.

Diagnosing and being aware of implementation

The case was proposed as a thesis project, where the goal was to alleviate the high workload of the HR department by deflecting incoming tickets. The HR department had *recognized* that the workload was high, and wanted possible solutions. Two solutions were already proposed. First, a chatbot was suggested, based on an existing project that was occurring at the consumer side of TelCo. Second, an automated e-mail answering system based on the concept of a consulting company was introduced. This is the context where LMA entered TelCo. The chatbot and e-mail automation came from a *search* routine looking for possibilities to reduce the workload, where both internal and external information was used. The chatbot was inspired by a solution already implemented at the consumer end of TelCo, and the e-mail automation solution came from a pitch by a consulting company at TelCo.

At this point, the HR Analytics team decided to hire LMA to provide insights into these found solutions. Based on the given options, LMA first *decided* to *diagnosed* the issue to find if the suggested solutions would solve the issue at hand; whilst two solutions were suggested that could reduce the workload of the HR department, the actual choice at hand was for a solution to reduce the number of tickets arriving at the HR department. Based on this, LMA changed the scope and *searched* for more interventions that could be done in the process to reduce the workload of the HR department, such as improving communications or improving the ability of HR employees to process answers, but also alternative solutions such as a chatbot or an automated question answering machine.

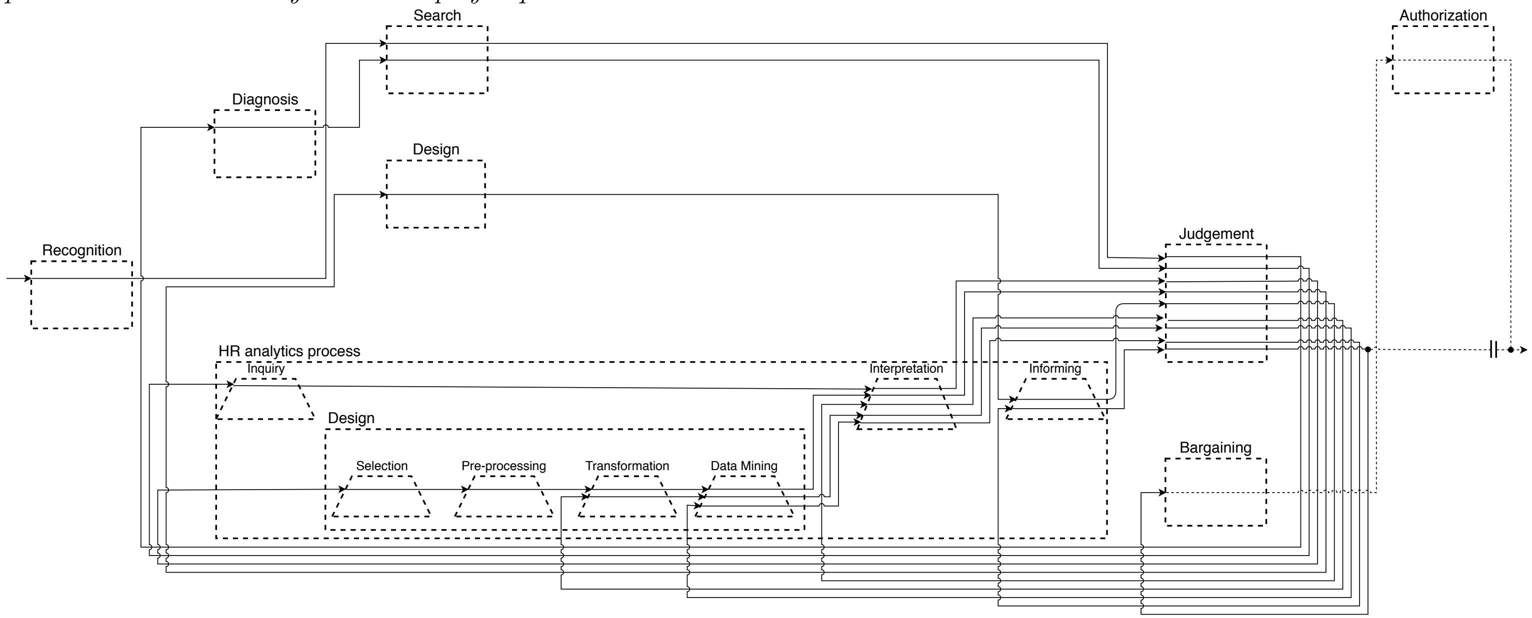
The implications for both HR employees, as well as regular employees, were identified early as a result of the diagnosis and search routines; HR employees would experience a change in workflow, and employees would experience a change in how their questions would be answered. This led to a change in scope for which solutions could be found, where a potential solution would not only be able to classify questions and answer them to reduce workload; a solution would be build that would allow HR employees as well as regular employees to give feedback such that the solution would work best for them.

Here, diagnosis and search gave insight into the requirements for the implementation of the solution. Not only the implications for employees and HR employees were identified, but also the systems in which the HR analytics outcome had to be implemented. This allowed for an early investigation into what was necessary to make the solution work conceptually, assuming that the HR analytics outcome, a statistical model that could help to answer employee questions, would work.

No good data quality to support the solution

The results of the diagnosis and search routine lead to a *judgement* by stakeholders from the HR department and the HRA team. This judgement was to choose for a question answering system opposed to a chatbot, due to the ability to automate the maintenance of the question answering system and the low costs related to developing the system opposed to existing chatbot solutions.

Figure 7: *An accepted design decision process with interrupted implementation, regarding a statistical model that can classify employee questions to automatically answer employee questions.*



Moreover, this solution would be implemented directly in the tool in which HR employees would also be working instead of e-mail, making it easier for HR employees to interact with the final solution. LMA was *inquired* to create a minimum viable product for the decision-making system, which could answer a small amount of frequently asked questions by employees.

Based on the initially identified solutions, LMA had assumed that data labels would exist within the dataset, to be able to create such an automated question answering system, especially since various decision-makers were present when deciding for the solution. Moreover, during the selection of the solution, the e-mail automation solution was already presented with a set of frequently asked questions it would be able to answer. These frequently asked questions, however, were not based on actual data, but an assumption of an HR employee passed to the consulting company pitching the e-mail answering system, which suddenly gave legitimacy to these categories without any solid arguments.

When the actual data arrived and LMA, and an *interpretation* occurred on the raw dataset, LMA realised that the labels present were not suitable for the use case. Following this, LMA *judged* that it would still be possible to generate these labels in some way, and *selected* and *preprocessed* the data required to generate these labels, which involved existing categorisations, answers given by HR employees and questions asked by employees and filtering some of these categories, questions and answers.

This was followed by a *transformation*, where the most important textual features in this data were used to develop a first primitive data model. A *statistical model was developed* that would show important textual features in the answers and questions that would relate to frequently asked questions, and based on the *interpretation* of this information, LMA *chose* to *design*, together with the HR employees, a set of 11 question labels for frequent questions the resulting solution should be able to answer.

These questions were selected due to the low risk they would have when answered wrong, but the relatively high impact when being able to automatically answer them. This assessment requires knowledge about HR practices and the potential consequences of answering a question wrong. For example, answering questions wrong about salary could result in legal consequences. Here, the importance of knowledge about the HR domain when performing analytics emerges.

Designing with implementation in mind

In the meantime, LMA was also involved in *designing* the actual implementation of this statistical model into the organisation. Several options existed, for which LMA chose to implement the statistical model through a Cloud solution that would integrate with the existing Cloud platform through which the HR department was providing answers to tickets, which was identified during the diagnosis routine. Together with the stakeholders of the HR department, HRA and now also the team that would develop the Cloud solution, referred to as team Cloud, made a *choice* to cooperate with team Cloud and use the question answering system as a use case to show the business the benefit of both the Cloud in terms of cost, and the benefit of HR analytics for operational efficiency.

Several minor design choices of how the HR analytics outcome would function in the Cloud was done iteratively as the HR analytics outcome evolve. Moreover, HR employees provided feedback when being involved in the design process of the statistical model, expressing their concerns. However, the strategic choice to go for a Cloud model occurred at the same point as the design choice for a set of questions. At this point, stakeholders of this HR analytics outcome were *informed* with regards to the changes in design, and *accepted* the change to the expected HR analytics outcome.

Overcoming data quality issues

Based on the choice to accept the adapted design, and thus HR analytics outcomes, LMA *interpreted* the data in the context of the questions and *decided* that the right course of action was to develop a statistical model that would show some results as soon as possible, to proof the business that the use case was going to yield results. At the time, the stakeholders of TelCo only knew that LMA was developing some kind of chat solution or Artificial Intelligence, with no knowledge about any further implications or issues with the labelling yet.

First, LMA iteratively *designed* a *statistical model* using a specific *transformations* that would aid the generation of labels for the dataset based on the identified 11 questions with HR employees. *Interpreting* the amount of generated labels and the statistical model's ability to suggest new labels, LMA *decided* to develop a full statistical model that could yield some initial results.

Showing both operational and strategic benefits

After *interpreting* these results and seeing a good performance, LMA *decided* to inform the business about the success thus far. This resulted in a positive response, as the real operational value was shown as a consequence of implementing the model.

But this was not the only thing that interested the business. LMA, due to the HR background, also showed the potential to track, real-time, the employee issues at hand, the ability to change communication based on new incoming questions, the ability to suggest answers to the HR department, and did so in a way that represented both operational value as well as strategic value to the HR department. These design choices emerged due to taking the final implementation in mind as well as the concerns of HR employees on how the system would work with them. This combination of strategic value, operational value and involvement of employees led to the embrace of the project, leading to increasingly positive views and expectations regarding the project from HR employees and stakeholders of TelCo. Not only this, but the general perception of HR analytics became more positive.

> I'm convinced that what you are currently doing with AI, which in terms of FTE and euro has a enourmous business case, but not only with regards to efficiency, but also in investing possibilities.
>
> - *HRAM*

This project had introduced a next step in the HR analytics practice of TelCo, were at first, analytics involving statistical models such as machine learning was done by the actual Analytics Department. This can be attributed to the fact that LMA is not only educated in HRM but also in Data Science and IT, leading to a mixed profile that enabled the use of the latest statistical techniques whilst also fully grasping the context of HR.

During the HR analytics process, HR knowledge was involved during inquiry, interpretation and informing; at these point in the process, it was required to put the results of the model or the choice to develop the model in an HR context, 'what are the benefits of doing this for HR?', 'How will HR employees use this tool?'.

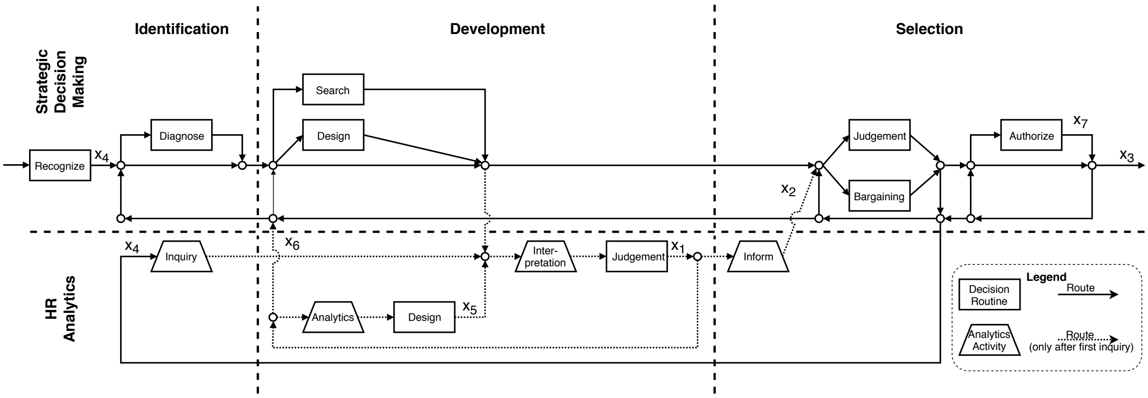
Trouble during implementation design

The further realization of the HR analytics outcome, however, is currently *interrupted*, due to team Cloud not having enough capacity to work on the solution. This is the consequence of outsourcing the final implementation of the solution, where the separation of motivations to create HR analytics outcomes emerges. This might lead to a political *design* choice to hire an individual for team Cloud that would work solely on the implementation of the HR analytics outcome. Moreover, due to the HR Analytics outcome requiring the use of sensitive employee data, a *bargaining* procedure has started with the privacy office to identify necessary design decisions required to meet authorization criteria.

4.5 Enactment of SDM characteristics by HR Analytics

During these cases, exploration was done to find ways in which HR analytics enacts Strategic Decision Making characteristics, with the intention in mind to also find potential influences on the enactment of these characteristics. In this section, several discoveries related to the enactment of SDM characteristics by HR analytics are presented.

Figure 8: *A modelling of Strategic Decision Making with an Analytics process.*



To visualise the enactment of characteristics of the SDM process in the context of HR analytics, an extension is made on the model of Mintzberg et al. (1976). Here, the analytics activity is visualised as a parallel process that can interact with an SDM process after being invoked by the SDM process through inquiry. Moreover, this model is extended with activities to illustrate what happens in the analytics process to get an HR analytics outcome. This model is shown in figure 8.

Moreover, various enactment of HR analytics characteristics and the SDM process and various contextual interactions have been identified in the three case studies. These are discussed in the following sections and are shown with the marks ‘$x_{<}number >$’ aside various paragraph headers. The discoveries presented in this section are based on the exploration through the three case studies.

4.5.1 Interpretation and Judgement

The interpretation activity came forward during the interview with AA, TAR and HRA1 as an activity that involves a reflection on existing information that emerged from the data to transform this information into knowledge. As part of the HR analytics process, interpretation always resulted in a judgement choice on action to do one of two things; either an action to change the HR analytics outcome, resulting in a new iteration of development or an action to inform stakeholders about the HR analytics outcomes or a required change to the expected HR analytics outcome.

Interpretation enacts judgement (x_1)
In case 1, interpretation led to a change in the design based on the selection of available variables, which consequentially led to the stakeholders being informed, as this change in design would impact the HR analytics outcomes by not only giving insights but in a predictive manner on a much more detailed scale.

In case 2, the business was informed after AA judged that based on the interpretation of the data and findings related to the required implementation, the desired HR analytics outcomes, which was a model that could predict the best mechanic to send for a task, would be incomplete without considering the implementation of the solution, resulting in a different HR analytics outcome, requiring a different amount of effort.

In case 3, the business was informed after the knowledge gap of the inquiry was sufficiently filled in, which was based on finding proof that automated question answering would be a viable solution to improve HR operations.

Thus, HR analytics is not only a process which creates value from data to answer a knowledge gap, but HR analytics is also inherently an iterative process that either identifies actions to take to improve HR analytics outcomes or identifies required changes to the desired HR analytics outcome, until the current desired HR analytics outcome is achieved. This shows that on an individual level, evaluation through interpretation always results in a choice to iterate or change an existing state.

Intellectual Capital affects Interpretation–Choice-Iterate (x_1)
The iterative nature of the HR analytics processes as a consequence of the limited ability to interpret and the following judgement choice in these cases is characterised by the inability to fully grasp the information that is currently available. This is expected to become increasingly troublesome with more data, as data quality problems and a lack of documentation of information in terms of universal knowledge require an organisational search to discover the underlying relations and meaning of metrics in data. In these cases, knowledge and experience gave analytics practitioners reasons to question what was in the data or to discover if there was more information available.

The cases suggest that the inability to interpret the data using conventional statistical technique is due to a lack of formalised processes when the data is created, causing data quality issues such as lacking definitions or consistency. Whilst personal experience and knowledge can partially overcome these issues by inferring knowledge from similar situations, a social network from which the reality behind the data can be inferred seems to help the most. Take for example case 2: AA finds strange entities in the data such as codes or outlier values and cannot explain them, thus AA, through the network of AM, finds the right person that can explain the reality behind the data, providing AA with the ability to interpret the information and create the right knowledge to make a judgement.

4.5.2 Informing and Judgement

The informing activity came forward after a design choice or a judgement choice made after an interpretation activity. Informing is characterised during the cases as an activity that involves the transfer of subjective knowledge to either fill in the knowledge gap as part of the HR analytics outcome or alteration of the expected HR analytics outcome.

Informing enacts Judgement (x_2)
In all cases, informing the stakeholders required the presentation of the subjective knowledge of the findings of the HR analytics practitioner to universal knowledge understandable by the stakeholders, and judgement on the expected HR analytics outcomes was made by the stakeholders. Moreover, the

In case 1, HRA1 informed HRAM about the design choices that would alter the expected HR analytics outcomes. Here, HRAM misunderstood HRA1, where the judgement was made that these new HR analytics outcomes would not significantly alter the scope of the overall SDM process by assuming generalizability of the found interventions to prevent turnover from the specific employee group to other employee groups, whilst HRA1 understood that this was not the case. Moreover, after the authorization of an altered expected HR analytics outcome was denied, the required effort to achieve a new HR analytics outcome was deemed too large to fit in the workload of the HR analytics practice, resulting in a discontinuation of the project.

In case 2, AA informed the stakeholders multiple times about a required change in expected HR analytics outcomes due to the interpretation of the data in the context of new knowledge. This new knowledge was related to data definitions and outliers and the eventual implementation of the HR analytics outcome. Here, the stakeholders first decided not to change the expected HR analytics outcomes to quickly find out what would be possible. Later, when the expected HR analytics outcomes had to be changed, the required effort to do so was deemed too large by one of the involved parties compared to the benefits, resulting in a choice to discontinue.

In case 3, LMA informed the stakeholders about the expected HR analytics outcome after the first design decision for the 11 question types the solution would be answering and the fact that the solution would be operating in a cloud solution, which altered from the initial expectations of the HR analytics outcome, that would merely be a statistical model that could answer basic questions.

Whilst the alteration of expected HR analytics outcomes as a consequence of informing is a characteristic of a diagnosis choice, this study argues that this is not the case, as the overarching problem the HR analytics outcome attempts to solve did not change after inquiry. Argued is that after the initially expected HR analytics outcomes and every subsequent change to this outcome all continue to serve the same goal as the context which the initial HR analytics outcome should solve.

Moreover, the informing activity and following choice illustrates that a pooled evaluation is made resulting in a choice to either accept the required changes in the HR analytics outcome or reject it based on the perceived amount of effort required to perform a next iteration of development, and based on the expected impact of the changed HR analytics outcome with respect to the initial goal of the SDM process invoking the HR analytics practice.

Informing-Judgement is affected by Human and Social Capital (x_2)
As informing is the translation of the subjective knowledge of the individual to universal knowledge understandable by stakeholders back to subjective knowledge of the stakeholder such that the stakeholder can make a judgement, human capital plays a large part in the enactment of judgement characteristics by informing. This works two ways, from the perspective of the informant as well as the perspective of the stakeholder.

The informant must understand the context in which the HR analytics outcome exists, which is the desired SDM process goal as well as the required effort and resources to achieve the HR analytics outcome, and the stakeholder must understand to what extent the expected HR analytics outcome will aid this goal in order to assess if the required effort and resources are worth investing.

The latter is also where social capital comes into play. The relation of HR and its analytics practice with relation to the rest of the business partners involved as stakeholders in the decision-making process weighs into the trust element that comes when coming to subjective knowledge. If an HR analyst believes that the HR analytics outcome is worth investing as it would lead to side effects such as increased employee engagement which the HR analytics practice is unable to provide quantitative evidence for, stakeholders from other business units or even within HR have to trust the practice on this value assessment. As a result, it is expected that the stronger the relational position of an HR department is within an organisation, the more unquantifiable effects of expected HR analytics outcomes will weigh against the required efforts to achieve these outcomes. This phenomenon is derived from case 2, where the HR analytics practice sees outcomes such as improved performance and growth of mechanics, but is unable to quantify these potential effects, causing the Analytics department to cling to the quantifiable financial effects when evaluating the required effort of change in the HR analytics outcome in the form of new requirements to implement these HR analytics outcomes.

Informing-Judgement enacts characteristics of e-HRM (x_3)
In all cases, the implementation of HR analytics outcomes in practice resulted in the enactment of characteristics of e-HRM, as most of these outcomes had to interact with existing IT solutions. For example, in case 3, characteristics of technology adoption prevalent in e-HRM occurred, where perceived utility to aid the job and ease of use by the end-users eased the acceptance of the expected HR analytics outcome.

Moreover, the perceived HR analytics outcome seemed to be judged similarly to e-HRM outcomes, in operational, relational and strategic benefits, whereas operational outcomes were formulated in increased efficiency, relational outcomes were formulated as the increased legitimacy of the HR analytics practice and strategic outcomes were formulated as improved insights that would aid strategic decisions.

The perceived effort formulated for the expected HR analytics outcome as well as the evaluation of the expected HR analytics outcome depends on the type of value the stakeholders expect. In case 2, the Analytics team expected operational benefits, whereas the HR department also saw relational benefits in an increased legitimacy of the HR analytics practice due to a successful project, and moreover, saw strategic benefits through new ways to improve learning and growth for mechanics.

In case 3, the initially expected HR analytics outcomes were operational, as the efficiency of the HR department would improve, but later on, relational and strategic value also started to get realized, where the relational value might have, similar to in case 1 and 2, already been expected a priori. The strategic value was only realised after the design choice was made to label questions based on their type, to give more specific answers to end-users. This suddenly allowed for the tracking of what type of questions employees were asking when and even allowed for historical analysis. As even strategic value was created, the business grew more enthusiastic about the results.

Overall, this also indicates that HR analytics outcomes can be of operational, relational and strategic value. Whilst the initial intention might be of the value of the types strategic, operational, relational or any combination of the three, the result of expected HR analytics value is always evaluated at the point of informing, influencing the choice to implement an HR analytics outcome or adapt the expected HR analytics outcome.

4.5.3 Inquiry and Judgement

The inquiry activity is seen as an activity sets the first expected HR analytics outcome, and solidifies the scope in which the HR analytics outcome will exist, involving the expected input from the HR analytics process to aid in an SDM process. In none of the cases, a completely new inquiry for the HR analytics process was made. Moreover, inquiry always led to the first interpretation-judgement.

Inquiry enacts Judgement (x_4)

The inquiry follows the choice to acquire the input of an HR analytics process to fill in a knowledge gap to aid an SDM process. This choice, except for case 3, results from the initial recognition by the stakeholders of an HR issue in the HR system that start the SDM process. During the inquiry activity, the transfer of the request to provide HR analytics outcomes always requires an interaction between the stakeholders and the HR analytics practice. A result of this interaction is establishing a mutual understanding of the knowledge gap at hand and how HR analytics can result in an outcome that could aid in this knowledge gap.

In case 3, LMA first performed a diagnosis and searched for alternative solutions to make an SDM decision on, but eventually also made the judgement with various stakeholders to utilise the HR analytics practice to provide input to the SDM process.

Human Capital and Normative Isomorphism and Inquiry (x_4)

The stakeholder makes the judgement to solve the knowledge gap with an HR analytics solution, and consequentially initiates the inquiry activity. For example, each case could have been solved with various solutions that would not utilise an HR analytics practice. A common denominator among these cases is uncertainty, where suddenly a rational normative approach to decision making is utilised when knowledge to make the decision has to emerge from data.

Furthermore, the HR analytics practitioner should fully understand the HR context of the inquiry to make a proper assessment during the interpretation activity to base a set of actions on that should lead to an expected HR analytics outcome.

From the stakeholders perspective, the inquiry requires the transfer of the knowledge gap to the HR analytics practice, based on some assumption about what the HR analytics practice could do. As can be seen in all cases, the judgement that HR analytics outcome will result in a filling of the knowledge gap is either grounded in the assumption that the data is there in some form, so theoretically it should work, or the assumption that an HR analytics case in another firm worked, so it should also work in the context of TelCo. Here, human capital played a role with regards to the knowledge and experience concerning HR analytics utility and required effort to perform the HR analytics process.

In case 1, a special type of assumption was made; there was some reasoning behind using the analytics practice, as another HR analytics practice of a mother had already performed similar analyses. During the HR analytics practice, this 'design' was quickly modified and changed to better match the SDM process knowledge gap that was identified during the inquiry.

Something similar happened in case 3, as existing tools and solutions existed that involved analytics that gave stakeholders the assumption that HR analytics would be the right approach to tackle their issues in the SDM process. Overall, the effects of normative isomorphism in the context of uncertainty emerge in the judgement leading to the inquiry activity.

In case 1, 2 and 3 the importance emerged of understanding the context in which the HR analytics outcome should be implemented. Understanding the impact on employees, existing HR practices and policies should be understood. In other words, the practitioner present at inquiry should understand the limitations and assumptions that need to be filled in to make the HR analytics outcome benefit the eventual HR system and the stakeholders of the SDM process. Knowledge and experience in the HR domain at this point is essential.

Social Capital and Inquiry (x_4)

In cases 1 and 2, another influence on the judgement leading to the inquiry can be identified, and that is the social capital of the HR analytics practice. The relational position at the time was weak, causing the HR analytics practice to show evidence of the value of HR analytics, causing the HR analytics practice to be inquired to provide input on several SDM processes in the form of the aforementioned cases. Suggested is that weak social capital within the organisation can drive the HR analytics practice to make a quick impact on the business to strengthen the relational position within the organisation.

4.5.4 Analytics Activities and Design

With analytics activities, the 'HR analytics activities' selection, pre-processing, transformation, metrics [6] and data mining are meant. These activities, in sum, formed an iterative process leading to various design choices, eventually leading to information that could lead to an interpretation activity. Whilst shown sequentially in visuals to show progression through these activities, jumping back in a sequence of analytics activities when entering the HR analytics process is continuously happening and part of the iterative nature of analytics.

Analytics Activities enact Design (x_5)

During these iterative analytics activities, continuous design choices are made that impact the eventual HR analytics outcomes. These decisions are based on the judgement on what sequence of actions is necessary from the HR analytics process to achieve certain HR analytics outcomes after interpreting the intermediary outcomes of a previous interpretation-judgement. This was described this way in cases 2 and 3, where these activities were present.

These design choices would impact the way HR analytics outcomes would be produced, but not the way HR analytics outcomes would be implemented. It involves the utilisation of certain data to extract the required information as the analyst sees fit. Here, only data related design choices are made with regards to the expected HR analytics outcome. In all cases, the results of the design choices isolated within the analytics activities always had to be interpreted to lead to a next step in the decision-making process. Moreover, only during interpretation was HR specific domain knowledge added in the context of the data.

[6] The derivation of HR metrics, whilst it did occur, did not only involve HR-related metrics but general metrics as well. Therefore, this name was changed to metrics in the model of case 2. Metrics were used to identify logical issues and in general to explore the dataset in a less extensive way than data mining, where one looks for emerging patterns.

Human Capital and Analytics-Interpretation-Judgement (x_5)
Overall, knowledge on how to perform analytics activities could be isolated to the analytics process, but during the interpretation of these outcomes, in all three cases, HR specific domain knowledge was necessary to take the next step to 1) interpret the outcomes of the analytics activities in the context of the expected HR analytics outcome and SDM process to see if the knowledge gap can be filled and 2) determine what would be required to fill this knowledge gap if the analytics procedure did not result in the proper outcome.

It is important to mention that the identification and quantification activities depicted in figure 2 are a unique element of HR analytics. These activities can be invoked as part of the HR analytics activity when no data is available, but require knowledge about the HR domain in order to properly identify what type of data could solve the knowledge gap at hand and knowledge on how this data can be quantified such that it can be fed to the rest of the analytics activities. When data is available, however, search and design choices on the strategic level can be made to aid further development.

Analytics design and other design or search choices (x_6)
The enactment of design by analytics activities did not extend to political design decisions or implementation decisions. Whilst relevant to the HR analytics outcome, these design choices involved either a way to achieve or implement the HR analytics outcome.

Case 1 shows an example of a design choice outside of the analytics activities that involved a political redesign affecting the way the analytics activities would be performed in terms of executor. Moreover, a second design choice changed the way the HR analytics outcome would be presented, in this case as a dashboard aggregating data instead of giving detailed individual reports, which classifies as an implementation of the HR analytics outcome. Other design choices emerged from the selection of data and affected the very nature of the expected HR analytics outcome.

Case 2 shows one design choice outside of the analytical activities in the form of a political design that arranges the cooperation between two departments, the analytics department under which AA would fall and the HR department who would provide budget and also evaluate AA on the development of the model in search for a gap in HR data.

Case 3 shows a design decision that affects the implementation of the final solution by running it in the cloud and allowing HR employees to add data to the final statistical model to improve performance of the implemented solution. This did not involve the design of how the data would be processed, but the design on how the expected HR analytics outcomes would be presented to the end-users.

Besides, case 1 and 2 showed a judgement that search was required instead of analytics as a next step to iterate on the HR analytics outcome. These require domain-specific knowledge from those creating or being responsible for the data to interpret the data or think about possibilities to overcome data-related issues that are not existing within the data already, such as looking for new information.

Finally, identification and quantification are seen as part of the analytics activities. This also makes the analytics activities of an HR analytics practice different from a regular data science practice deploying a KDD-framework, as these two activities are directly related to the people in an organisation and the data they produce.

Only an identification activity occurred to identify what data to look for in order to strengthen the analytical model of case 2. Quantification is therefore not a necessary follow up to identification as was visualised in figure 2.

4.5.5 Analytics activities and Authorization

In all cases, some form of authorization was or will be done due to the sensitive nature of HR data, which required compliance with the GDPR legislation. In case 1, this led to several blocks and redesigns necessary to continue the project, whereas in case 2, this authorization process did not result in any issues. In both cases, the criteria relevant to the authorization process were interacted with during the analytics activities, such as including or excluding certain forms of data to achieve a certain purpose.

Coercive Isomorphism influences analytics through Authorization (x_7)
Through the authorization decision-making process, the coercive isomorphic influence of legislation entered the strategic decision-making process, by limiting what data could be used during the analytics process. In case 1, the required change to the expected HR analytics outcome became too large, and together with already shifting business priorities, this led to a freeze of the project until the TelCo was willing to invest time into the expected HR analytics outcome.

5 Discussion

HR analytics has been criticised for not producing the right outcome. Arguments given are a lack of expertise in analytics, relations with the organisation and the tools to do analytics (Angrave et al., 2016; Marler and Boudreau, 2017). This study presents several findings that can aid both HR practitioners in improving their practices, as well as researchers in the HR analytics domain by defining a framework in which HR analytics can be studied in the context of decision making. Moreover, several contextual influences have been identified that influence the pathways taken in this framework.

This study uncovers that knowledge and the lack thereof plays an important role in the HR analytics process, but not always in the form of analytical knowledge or expertise. Whilst analytical skills do play a role in affecting the HR analytics process, domain-specific knowledge remains important. Several implications for human capital required to serve the need for domain-specific knowledge are given.

First, informing requires the transfer of the HR analytics outcome to the stakeholder, not only when the need of the stakeholder has been fulfilled, but also when the need of the stakeholder requires a change. Here, stakeholders only perceive so much of the knowledge being transferred by the HR analytics practice back to the strategic decision-making process. Having the skills to correctly transform findings into the required knowledge by stakeholders plays an important role in the HR analytics process. These findings coincide with (Mintzberg et al., 1976), who identified the limited ability of decision-makers to process knowledge, often due to the share volume of knowledge coming their way. Being able to transfer findings to decision-makers is expected to improve HR analytics outcomes.

Second, The emergence of human elements contrasts with the rational normative model in which analytics plays a strong role since it is a good way to find objective criteria to evaluate strategic decisions within an organisation (Hitt and Tyler, 1991; Huff and Reger, 1987; Ackoff, 1981; Igor Ansoff, 1986; Camillus, 1982). Our findings coincide with the findings of Hitt and Tyler (1991), in the sense that human interpretation of rational information plays an important role within this strategic decision-making process enabled by HR analytics.

Both inquiry and interpretation are activities that share characteristics with the LAMP model (Boudreau and Ramstad, 2007). An important difference with existing frameworks on HR analytics is the inherently iterative nature where the required knowledge of the stakeholder is evaluated in various ways. During this interpretation, strong knowledge of a specific HR domain is required. Here, all elements of the LAMP model return during the inquiry. Interpretation, however, is when a first look at the data is taken and one decides what to do next, to iterate, to inform, find new data, clean data or any other form of HR analytics activities. The framework in 8 captures this complexity. When the knowledge gap has been identified, however, it is up to an analytics process to cater to this knowledge gap. This means that advanced knowledge in how to perform statistical analytics is not an essential aspect of the HR role; it is, however, important to understand the possibilities and required effort to realise these possibilities concerning the knowledge gap.

From the second point, one might think that the analytics activity within the HR analytics practice can then be completely outsourced to an analytics department. However, the identification and quantification of people data are what makes HR analytics unique compared to other analytics practices. Our third point with regards to required human capital to yield better HR analytics outcomes refers to the ability of the HR practitioner to identify and quantify what data can aid the development of HR analytics outcomes. Whilst the identification activity has been described in the second case study, an analysis of the quantification activity is still missing. Future studies should investigate the required methodology and human capital to aid the quantification activity, as it is viewed as vital in emerging HR analytics practices where people data is not yet abundant.

Besides, the findings of this study suggest that identification and quantification do not necessarily follow each other as presented in figure 2; in case of data seems to be present in the integration, the quantification of data might be skipped in favour of a search for already existing data.

This is not the only deviation from the initial model of the HR analytics process made in figure 2. In this visualisation of the HR analytics process, the input to the SDM process is rather linear; HR analytics provides input to the SDM process, the HR System is improved, and depending on the effects, a new action is taken. Our study suggests that HR analytics is an iterative process that can iterate on either the methods used to achieve an HR analytics outcome or the HR analytics outcome itself, depending on the interpretation of an HR analyst. However, if one unrolls these iterative decisions, a sequence of decisions can be derived which can be presented in a linear model as in figure 8.

Moreover, this study uncovers the importance of social capital and the relational position within the organisation for the success of HR analytics. This coincides with the research of Marler and Boudreau (2017), who found that the relation between HR analytics and the network of supportive stakeholders. During this study, it was found that this manifests itself through the ability to find and acquire data within the organisation. Moreover, the reasoning behind peculiar findings in the data could be gained by checking within the social network of the organisation, providing a reality check to analytical results. Finally, this study suggests that the evaluation of the value of the expected HR analytics outcome from the HR analytics practice can translate stronger in case of a better HR relation with other stakeholders.

Whilst social capital can aid in finding explanations in data, organisational capital, or the lack thereof, resulted in data quality issues due to a lack of formalized ways of storing and defining the data. Data quality issues found were accessibility, representational, intrinsic and contextual, coinciding with the findings of Wang and Strong (1996) on the meaning of data quality. Here, the lack of formalized processes and procedures made it difficult to acquire data and to interpret data as is, without invoking the social capital to give more input on the contextual meaning of the data, what the elements of data represented or the strange intrinsic value of some data. Suggested is that formalized processes for storing and acquiring data to improve data quality can not only improve the quality of HR analytics practices, but also the speed of the HR analytics practice due to lower dependency on the social network of the organisation and related knowledge transfer sessions.

Evidence was found for institutional isomorphism, similar to the study of Angrave et al. (2016), but in a different form. In times of uncertainty, people will choose a solution that worked for others or in familiar situations (Mintzberg et al., 1976). Evidence of this was found in case 1, where not only HR analytics was chosen as a way of input to the SDM process, but also the method of analytics and subsequently expected HR analytics outcomes. Moreover, during authorization, due to a lack of knowledge about the impact of the HR analytics outcome, the privacy office caused a coercive isomorphic force on the HR analytics practice, limiting the way the practice could run by not allowing certain data to be used.

The mimetic isomorphism found by Angrave et al. (2016) was worded as the choice to adopt similar systems and tools to perform HR analytics. Whilst systems and tools are relevant to the implementation of HR analytics outcomes, no evidence was found for isomorphism related to tools or technology. In terms of the Resource-based value approach to HR, a unique value can thus still be generated by HR analytics practices due to the exclusiveness of their data, representing unique value that other organisations cannot utilise (Barney, 1991).

Whilst various rational influences on the enactment of HR analytics on the SDM process have been given, irrational influences or ways of thinking have been left out of the analysis. Whilst irrational beliefs and influences such as emotion have a proven effect on decision making (Kramer and Block, 2007; Koenigs and Tranel, 2007), research in this area remains quite limited. Due to a lack of foundation for a model relating HR analytics with decision making and limited research, irrational beliefs have been left out of scope for this analysis, but provide ground for future research into the irrational influences on the enactment of HR analytics on the SDM process.

What was found is that the way HR analytics outcomes are implemented behaves similarly to technology implementations in HR from e-HRM literature. Evidence was found for a separation in operational, relational and transformational value being associated with HR analytics outcomes, similar to e-HRM outcomes (Ruel et al., 2007; Ruël et al., 2004; Wright et al., 2001; Lepak and Snell, 1998). Moreover, the issues that arose with relation to the implementation of HR analytics and the perceived value of the HR analytics outcomes based on this implementation was often done in technology, but not based on the behaviour of other organisations. This perceived value and implementation again showed characteristics present in e-HRM literature on similar topics, such as the importance of ease of use or taking into account the end-user during development (Ruel et al., 2007; Bondarouk and Ruël, 2013).

6 Limitations

Throughout this study, recollections of peoples experiences have been used to gather information about the three presented case studies. Retrospective studies are not uncommon in qualitative research and are a valid approach in studies related to decision-making (Mintzberg et al., 1976; Aharoni et al., 2011). However, it can introduce recall bias. By interviewing a variety of people and throwing technical action research in the mix of methods used during this study, this recall bias will not affect the resulting model in figure 8 and subsequent interpretation of relations presented in the model and contextual influences.

The low amount of participants in the interviews for this case study might cause concern. During the semi-structured interviews snowball sampling was utilised, where the researcher finds new interviewees through the contact information that is provided by other interviewees (Noy, 2008). This type of sampling technique allows the researcher to find those relevant to the study that could not be found a priori. As discussed in the method section, using this sampling technique ensured that those relevant to the decision-making process were interviewed; a more complete picture from the perspective of the HR analytics practice cannot be sketched of the cases. Whilst a limitation of snowball sampling is the necessity of a complete social network, a larger network could not be reached as only those in the decision-making process had to be interviewed, of which the relevant decision-makers and analysts were addressed and interviews, as there were no declinations to any of the interviews.

Finally, this study was done in the context of an HR analytics practice. There is no reason to believe that an HR analytics practice that deploys the accepted definition of HR analytics will cause a different result than presented in this study.

7 Conclusion

This study has developed a framework in which HR analytics can be analyzed concerning strategic decision making in an organisation. This framework describes the process through which HR analytics is expected to enact on routines in the strategic decision-making process, describing what routes should be followed to invoke such a decision making processes, but also what decision might be made that affect the outcomes of the HR analytics practice. As organisations are attempting to become more and more data-driven in their decision making, this framework can aid in the realisation of this ambition by describing how this data-driven decision making emerges in the context of HR analytics.

Moreover, several contextual influences have been identified that affect the ability of the HR analytics practice to aid stakeholders in the practice in making an informed strategic decision in the context of an HR system. Effects from intellectual capital, institutional isomorphism and e-HRM are described.

Evidence is found for a need for a variety of human capital within an HR analytics practice. During the inquiry, the knowledge and experience should be present to evaluate the expected HR analytics outcome of a stakeholder in the context required effort, feasibility and impact on the HR issue at hand. During analytics, knowledge and experience on data selection, pre-processing, transformation, metrics and data mining should be present to extract information from data, if available. Otherwise, these have to be identified and quantified, requiring insight into what type of data is missing, but also how to capture this data in a manner that can result in information that can solve the knowledge gap. The identification and quantification separate the analytics activities of HR analytics practices from more general analytics practices.

During interpretation, one should be able to interpret the new or available information within the HR analytics practice in the context of the expected HR analytics outcome, and decide what action should be taken; iterate and develop new information or inform stakeholders on a required change to expected HR analytics outcome or ideally, inform stakeholders with knowledge that fulfils the expected HR analytics outcome. During this informing, knowledge and experience is required to properly translate the found knowledge to stakeholders, who have a limited understanding of the analytics process and the data.

Overall, knowledge of statistical techniques and how to apply these to data to extract information is required, as well as knowledge and experience in identifying and quantifying people-related data. Moreover, understanding the needs of stakeholders, interpreting analytics outcomes in the context of the stakeholder needs and informing the stakeholders about these results requires knowledge and experience in the HR domain under which the stakeholder needs fall.

Future research can investigate these identified required human capital and their manifestation in practice in terms of roles and fulfilment. This will provide HR practitioners not only with the knowledge required to run an analytics practice but also practical examples of required skills to improve hiring and growth of potential HR analysts.

The need for social capital for HR analytics emerges in two ways. First, social capital in the form of the relational position of the HR analytics practice within the organisation can aid in the trustworthiness of relational and strategic value of expected HR analytics outcomes to other departments of the organisation who are inclined to focus on operational value. Second, social capital through social network proves useful to overcome data quality issues. These data quality issues emerge as a result of lacking organisational capital in the form of standardized ways to register, define and access data. Future research should be done in the ways data quality issues can be prevented through either an improvement of organisational capital or social capital. This can provide HR analytics practices with useful insights to improve their practices.

The implications of memetic isomorphism through normative isomorphism and coercive isomorphism emerged in this study. Future research should investigate how these forces differ in another national context, like the GDPR, an EU specific legislation, heavily impacted the ability to perform HR analytics. Moreover, the impact of normative isomorphism might be an explanation for the general discourse around a lack of analytical skills among HR professionals compared to other social domains such as marketing. Future studies should evaluate the effects of normative isomorphism on the choice to adopt certain HR analytics models.

Finally, the similarities to e-HRM in terms of implementation en outcomes provides interesting research directions in both domains. Implementation of HR analytics outcomes seems to depend on technology, which comes with the implication that HR analytics outcomes depend on similar variables, such as ease of use and expected benefits by the end-user, as with e-HRM implementation. Moreover, HR analytics outcomes seem to come in similar types as e-HRM outcomes, operational, relational and operational.

This opens up future research to investigate the effects of e-HRM on HR analytics outcomes. This study has a small example of the required effort to implement an HR analytics outcome in a present technological solution. This example can serve as the start of studies that can investigate the interrelation between HR analytics and e-HRM. How is e-HRM an enabler for the creation of certain types of value emerging from the HR analytics process?

8 Acknowledgement

I would like to thank my supervisors at both the University of Twente and TelCo for supporting me, listening to my findings and challenging me in my logic and theories. The freedom and trust I have been given continuously motivated me to push the research further. My thanks also go out to the interviewees, who provided invaluable input to this study. Without you, this would not have been possible.

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