Informating HRM through »Data Mining«? A Conceptual Evaluation

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Abstract. Beyond mere automation of tasks, a major potential of HRIS is to informate HRM. Within current HRIS the informate function is realized based on a data querying approach. Given a major innovation in data analysis subsumed under the concept of »data mining«, possibly valuable potentials to informate HRM are lost while overlooking the data mining approach. Our paper therefore aims at a conceptual evaluation of the potentials of data mining to informate HRM. We hence discuss and evaluate data mining as a novel approach compared to data querying as the conventional approach of informating HRM. Based on a robust framework of informational contributions, our analysis reveals interesting potentials of data mining to generate explicative and prognostic information and hence to enrich and complement the querying approach. To deepen the knowledge on the contributions of data mining we finally derive recommendations for future research.

1 Introduction

The usage of Information Technology (IT) in Human Resource Management (HRM) is wide spread in the interim and corresponding Human Resource Information Systems (HRIS) provide a broad range of functionalities to support HR tasks. Current systems cover operational HR tasks such as payroll processing, employee and contract record keeping, attendance administration among others [e.g. 1, 14] as well as managerial tasks such as recruiting and selection [e.g. 18], compensation and benefits [e.g. 7], training and development [e.g. 34], performance management [e.g. 22] and HR planning [e.g. 9]. Insofar, current HRIS aim at comprehensively automating and informating the operational as well as the managerial side of HRM [31].

Traditionally, HRIS are applied to automate HR tasks and thus enable efficient task fulfilment. To give a plain example, payroll systems allow the automated calculation and payment of salaries thereby easing the burden of a manual payroll processing. Generally, automation hence enables efficient realisations of diverse HR task thereby speeding up processes, reducing error ratios, and lowering costs of task fulfilment. Given these advantages, the automation of HR tasks via HRIS offers extensive potentials for HRM.

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Notwithstanding these advantages, a second and by far more advantageous function of HRIS is to informate HR managers so as to improve their operative as well as strategic decision making [35, 36]. As HRIS are already widely applied to automate HR processes, extensive and ever increasing data pools underlying these processes are mandatorily stored in the database layer of any HRIS configuration. Thus beyond automation, the unique value of HRIS lies in their capacity to analyse these large amounts of data and support HRM with valuable information that will lead to better, since more informed managerial decisions and actions. Hence based on automation it is essential to exploit the potentials of HRIS to informate HRM thereby improving HR practices and enabling a proactive and strategic HRM [12].

From the beginning of HRIS usage, conventional reporting features of HRIS provided possibilities to informate HRM by offering a broad variety of individually specified as well as generally preconfigured data queries. Though there are improvements such as multidimensional data analysis [5, 19, 24] up until now queries generally represent the common realisation of the information function in current HRIS.

However, given the persistent progress in information science, in the interim innovative methods of data analysis are available that aim at the automatic recognition of data patterns and hence at providing new, valid and potentially useful information beyond mere data queries [8]. Metaphorically, such methods are subsumed under the concept of "data mining" so as to demonstrate the "digging" of valuable information out of databases and data storing components of application systems. Synonymous terms are "knowledge discovery in databases (KDD)" or "data pattern recognition" [8]. First applications of data mining in diverse areas of HRM show promising potentials of mining HR data [e.g. 6, 10, 11, 16, 23, 26, 27, 28, 29]. However, the application of data mining in the context of HRM is scarce and innovative, and data mining is far from being a standard analysis instrument of current HRIS. Given the outstanding importance of the informate function of HRIS, the question arises whether valuable potentials to informate HRM are lost by overlooking data mining [21]. Hence, our paper aims at a conceptual evaluation of the potentials of data mining to informate HRM.

To do so, we firstly discuss conventional data querying and novel data mining approaches to informate HRM. Based on a robust framework of information contributions we subsequently evaluate both approaches on a conceptual level. Conclusively, we attempt to derive recommendations for future research in order to elaborate the potentials of data mining to informate HRM.

2 Presentation of Approaches

Using the data pools of HRIS to informate HRM is by no means a new claim. On the contrary, from the beginnings decades ago HRIS were (also) used to informate HRM. As already mentioned, the conventional approach of informating is data querying, while data mining constitutes an innovative approach that possibly shows diverse advantages. We hence analyse both general approaches in the following so as to elaborate commonalities and differences of querying and of mining HR data. However, since both approaches comprise of several different categories of analysis methods, a comprehensive comparative discussion of all categories is beyond the scope of this paper. Hence, with standard queries and classification analysis we choose two prototypical methods of each approach and discuss their procedures and possible results. Strictly speaking, this focus restricts our comparison of querying and mining to the respective categories. Results hence cannot be plainly transferred to the general approaches of querying and mining. Nevertheless, a first comparison of prototypical methods is provided and further querying and mining methods can be discussed analogically.

Since particularly data mining methods are rather complex we additionally base our analysis on a plain example so as to increase intelligibility. A high turnover rate implies intensified recruiting and development efforts among others. These measures lead to high costs, thus informating HRM to create retention strategies is of unmistakable importance. Therefore, we focus on turnover analysis as an exemplary application area in the following.

2.1 Data Querying

Since employed for decades, data querying constitutes the well-established approach of informating HRM. Roughly distinguishing different categories, “standard queries" and “multidimensional queries” constitute two major categories of data querying. *Standard queries* represent precise requests for information that use search values combined with operators to specify the information needed. They are the exceedingly common method of retrieving information out of structured data and are offered by (nearly) every HR application of whatever kind and area. *Multidimensional queries* (often also referred to as “Online Analytical Processing [OLAP]”) constitute a newer query approach that is based on a specific preparation of data in n-dimensional cubes (“hypercubes”) and allows analysing HR relevant figures in relation to several relevant dimensions [e.g. 5, 19, 24]. As a newer query category multidimensional analysis is offered only by few HR applications, as for instance data warehouse-systems [19]. Due to their prevalent usage to informate HR, we focus on standard queries as a prototypical query category in the following.

Technically, standard queries are realized based on common query algorithms or query languages such as Structured Query Language (SQL) [e.g. 17] respectively. Applying standard queries, HRM can receive information about historic and recent events concerning any HR related aspect stored in any system or component of the HRIS database layer. Applied to turnover analysis, standard queries are able to satisfy information requests that may be expressed by questions like

“How many employees have left the company during the last year?”,
“What were the demographical attributes of these employees?” or
“What were the exit kinds of these employees?”

If not offered as a general predefined query, users have to specify such information needs based on an individual query by firstly determining desired data items while additionally stating desired values of certain data items by using operators and reference values. To satisfy the information requirements delineated above, a query can be specified to display the items like name, gender, age, and exit kind among others while selecting only records of employees that have left during the last year. After specification the query is executed and results are usually presented in tables. The following figure depicts a conceivable result of such a query.

name	gender	age	qualification	...	exit kind
Smith	m	45	high	...	employee's reason
Kline	f	59	medium	...	early retirement
Pitt	m	34	medium	...	employee's reason
Jolie	f	56	high	...	early retirement
Tarantino	m	65	high	...	regular retirement
…	…	…	…	...	…

Fig. 1. Example of a data querying result.

Additionally, sorting functions may be applied to sort records with regard to gender, age or exit kind among others. The general benefit of querying then lies in the ability to filter the required information out of often huge amounts of data and present it in a clearly arranged and hence easily intelligible form. Generally, standard queries are able to satisfy information needs of HRM that can be clearly specified, concern historic and recent information, and are represented by corresponding data items stored in the data layer. Hence, as a first requirement, users must be able to concretely specify the information needed. While sounding trivial at first glance, specifying concrete information needs of HRM is often intricate. If, for instance, employees of a certain ethnic category unexpectedly are significantly more frequently quitting, this important information will be lost in the query above, since the item "ethnic group" was not considered relevant and hence was not specified. Thus, queries show difficulties in detecting "hidden" and unexpected information represented in the data layer. Further, as a second requirement, the information needs which should be satisfied by queries usually refer to historic and recent information. If HRM, for instance, should be interested in a prognosis concerning which valued employees are likely to voluntarily quit in the future (so as to counteract with specific retention measures), querying is usually not able to provide such prognostic information. Admittedly, users can "manually" search for attribute patterns of typically quitting employees in the query result and use this pattern for a prognosis. Given usually copious rows within a query result, such a manual search is however at least intricate and laborious, if not impossible. Hence, queries are suitable for providing historic information but usually show difficulties in providing relevant prognostic information. Finally, a third and obvious requirement is the availability of data items that correspond with the information need. If HRM, for instance, is interested in concrete exit reasons of voluntarily leaving valued employees but corresponding data items are missing, querying evidently is not able to provide such information.

To sum up, data querying constitutes a well-established approach to informate HRM concerning historic and descriptive information.

2.2 Data Mining

Not yet established as a general measure to informate HRM, data mining offers the possibility to extract new, valid, understandable and potentially useful patterns in larger amounts of data [8]. Roughly distinguishing different categories, "classification analysis", "association analysis" "segmentation analysis" and "deviation analysis" constitute four major categories of data mining [e.g. 4]. *Classification analysis* aims at automatically classifying objects to predefined classes, thereby detecting those attributes that systematically discriminate between the classes. Classification hence contributes to information by detecting attributes that predict the belonging of an object to a certain predefined class. *Association analysis* aims at automatically detecting significant associations between the attribute values of objects. Association hence contributes to information by detecting connections and links in data. *Segmentation analysis* (frequently also referred to as "cluster analysis") aims at the automatic generation of homogeneous segments (groups or clusters) of objects. Segmentation hence contributes to information by revealing different homogenous groups within larger data pools. Finally, *deviation analysis* aims at automatically detecting objects that - for whatever reasons - significantly differ from other objects. Hence, deviation analysis contributes to information by detecting all kinds of "outliers" [e.g. 4]. Due to its prototypical character for data mining we focus on classification analysis (also referred to as "rule induction" or "decision trees") in the following.

Technically, classification analyses are realized based on classifier algorithms such as the C5.0 algorithm [25]. Applying classification analysis, HRM can receive information concerning attributes that - abstractly speaking - predict the belonging of an object to a certain predefined class. Applied to turnover analysis classification analyses are able to satisfy information requests that may be expressed by interrelated questions like

"What are significant attributes of employees who have left the company?",
"Why did these employees leave the company?" and
"Which type of employee is likely to leave in future?"

To answer these questions users have to specify objects and the classes, towards which the objects should be classified. More concretely, given the information request delineated in the above questions, a user will specify that employees should be classified to the different classes of the "exit kind" item, i.e. "regular retirement", "early retirement" and "employee's reason". Further specifications are not necessary, since the algorithm will automatically search for attributes that systematically discriminate between these specified classes. After executing, classification results are usually presented as a set of rules, each of them comprising of premises ("If"-component) and a conclusion ("Then"-component). The following figure depicts a conceivable (partial) result of a classification analysis formulated as a rule.

IF	age < 40
AND	total salary < 31.500€
AND	qualification = high
THEN	exit kind = employee's reason

Fig. 2. Example of a data mining result.

As can be seen from the rule, employees are classified to the class “exit kind = employee’s reason” (conclusion of the rule), while the attributes listed before are predictors of belonging to this class (premises of the rule). Hence, the information provided is, that a certain age, salary and qualification of employees induce voluntary turnover. Such rules then constitute the “pattern” that data mining has detected. As a first central difference to queries, these predicting attributes (as their values) have not to be specified by the user, but are automatically found by the classification algorithm out of a large amount of possible attributes of the corresponding database. Users hence need no previous knowledge or ideas concerning predictors of voluntary turnover. In addition, while queries deliver mainly descriptive and historic information, generated rules at least have the potential to provide explanations and allow forecasts. Accordingly, the rule delineated above offers a plain explanation for voluntary turnover: Since younger, high qualified persons with a rather low salary are leaving, the discrepancy between compensation and qualification offers an obvious explication of turnover. Moreover, assuming that the rule above represents a general explicative pattern it also allows a forecast of future turnover. Hence, if there still are younger qualified employees in the delineated salary class, this group is particular likely to leave as compared to other employee groups. Rules, however, do not automatically dispose of explicative and prognostic possibilities, but can also turn out to be merely descriptive resembling the results of queries in this aspect. The following figure depicts a rule concerning early retirement received from mining real HR data of a MNC.

IF country = Germany
AND age ≥ 52
AND age ≤ 56
THEN exit kind = early retirement

Fig. 3. Example of a descriptive data mining result.

This rule does not show the potential to explain early retirement. Rather, it reflects the regulations of early retirement legislation in Germany that allow early retirements exactly within the presented age group. Though commonly of lower value such descriptive information is not worthless, since for instance legal compliance can be controlled based on such rules. Explicative as well as descriptive rules then are valid outputs of classification analysis. Since classification algorithms select attributes based on formal but not textual relevance criteria, specific data constellations may also lead to invalid rules. Thus before further usage, generated rules in any case have to be carefully evaluated and interpreted against the corresponding real HR background [8], while especially the explicative and prognostic validity of rules has to be assessed.

Summed up, data mining is able to automatically generate new, valid, understandable and potentially useful patterns out of HR data. In the case of classification analysis, rules concerning any interesting phenomenon can be generated, that show the potential to explain the phenomenon under consideration as well as predict its appearance in future. Thereby data mining offers information that usually is unobtainable using mere querying of the same data.

3 Conceptual Evaluation of Approaches

Querying and mining of HR data both aim at exploiting the potential of existing data pools to informate HRM. To provide a first general evaluation and to basically compare the respective contributions of both approaches in informating HRM, we elaborate on a general framework that robustly categorises different categories of information necessary to informate HRM (as other units of the organisation).

As a first dimension of the framework, it is important to consider the *time-reference* of the information provided. Roughly dichotomising this dimension, historic and prognostic information can be distinguished. Historic information exclusively refers to developments of the past, while prognostic information refers to developments that are (likely) to come in the future. Assessing these categories, both kinds of information are traceably contributing to informate HRM. Initially historic information evidently contributes to informate HRM, since desired and undesired developments of the past can be controlled. All the more, prognostic information contributes to HRM, since it emphasizes relevant future developments. Concerning the derivation of appropriate management measures, however, prognostic information is more favourable, since adequate (counter-)measures can be taken in advance, while measures based on historic information necessarily happen after a triggering event and hence may be too late. Referring to the above example of unwanted turnover of a larger group of key employees, historic information is merely able to report such undesired developments in the recent past, while (valid) prognostic information at least offers the potential to prevent such developments. In brief, while mere historic information urges HRM into a reactive position, additional prognostic information facilitates a more proactive role of HRM.

As a second dimension of the framework, it is insightful to consider the *quality* of the information provided. Also roughly dichotomising this dimension, descriptive and explicative information can be distinguished. Descriptive information merely reports relevant developments without offering any background information (answers to “what”-questions). Explicative information exceeds this level since it additionally offers insights concerning the reasons or causes of the developments reported (answers to “why”-questions). Again, both kinds of information are obviously necessary to comprehensively informate HRM. Concerning the derivation of appropriate management measures, however, explicative information is evidently more advantageous, since it additionally explains developments thereby offering hints concerning kind, starting point and success of corresponding (counter-)measures. Referring to the above turnover example, descriptive information hence merely reports the fact of unwanted turnover, while explicative information gives an explanation and hints at possible retention measures as for instance changes in compensation. In brief, while mere descriptive information leaves HRM unadvised, additional explicative information usually offers some guideline for action.

The combination of both dichotomised information dimensions generates a robust and general framework with four quadrants that is able to evaluate information contributions of different analytical approaches (see Figure 4).

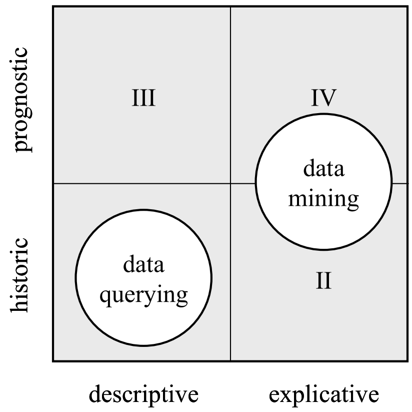

Fig. 4. Information dimensions and analytical approaches.

Classifying the delineated analytical approaches into the framework, the data querying-approach clearly belongs to the quadrant I, since it offers historic and descriptive information. By offering such historic-descriptive information valuable contributions to the informate-function can be achieved, as depicted above. Hence, now as before diverse categories of data querying should be used to informate HRM. However, the more valuable information quadrants II, III and IV with prognostic and/or explicative information usually cannot be served based on querying approaches of whatever kind. This hence constitutes an evident major limitation of querying. Given that querying currently constitutes the prevalent approach of informating HRM, even a serious analytical lack has to be stated.

As explained above and therefore suggested in Figure 4, data mining shows the potential of reducing this lack. Yet, again it has to be stressed that data mining does not mandatorily provide explicative and prognostic information, since for instance merely historic-descriptive information is also an imaginable result. Hence, the actual classification of data mining into the framework depends on the concrete single application and the corresponding concrete results of a data mining project, while all four quadrants generally are conceivable. The classification provided in Figure 4. therefore represents a successful application of data mining. Since the provision of prognostic and explicative information is feasible with (successful) data mining it offers a valuable and desirable completion of the current analytical approach, facilitating a more proactive role for HRM as required so often in research and practice.

To sum up, data querying and data mining constitute dissimilar analytical approaches that do not show rivalling positions since the kind of offered (or at least intended) information clearly differs. Data mining then plainly demonstrates the potential to complement and enrich current methods and corresponding information levels with particularly valuable additional information. Hence based on a first conceptual evaluation, data mining should be added to the standard inventory of analytical methods of HRIS in order to more comprehensively exhaust the potential of given data to informate HRM.

4 Future Research

Given the positive results of the initial conceptual analysis above, much research work remains to be done.

A first limitation of our work is the mentioned focus on prototypical categories of querying as of mining. Future research hence should broaden the scope of analysis by considering all relevant querying as particularly mining categories, for instance based on the framework above or on further theoretical groundings. This will assess and complement our statements and likely lead to a more comprehensive since more differentiated understanding of the potentials of data mining to informate HRM.

A second and perhaps more serious limitation is constituted by the mere conceptual character of our evaluation and hence the lack of empirical evidence. Consequently, the potentials evinced by conceptual analysis should additionally be empirically evaluated. However, the mere novelty of the data mining approach yields a major problem for any empirical evaluation, since there is no larger set of organisations that comprehensively apply data mining in HRM. While there may be a small number of pioneering organisations that may allow for initial case study approaches [30] any survey approach will be pointless since the only result will be that data mining is not adopted in HRM yet. Therefore, action research can be recommended as a proactive research approach [e.g. 33] also feasible and valuable in information systems research in order to examine research questions of practical and scientific relevance [e.g. 2, 13, 20]. Based on a cooperation of researchers and practitioners, action research generally aims at solving novel practical problems while contributing to corresponding scientific knowledge [3]. The practical problem under consideration then generally is informating HRM via adequate analytical approaches, while the corresponding scientific topic is constituted evaluation of diverse data mining approaches, as described above. Following a prominent suggestion, action research projects may be described as a process comprising of diagnosing, action planning, action taking and specifying learning [2, 32]. Diagnosing aims at the specification of the practical problem and the corresponding research hypothesis. During the action planning phase researchers and practitioners jointly specify the application area and choose the corresponding data mining method and the data to be analysed. Subsequently, the data mining analyses are conducted, and the results generated are evaluated by specifying the practical and scientific knowledge gained. Based on the knowledge gained, eventually a next iteration of an action research cycle can be established [2, 15].

One suggestion to structure this process is to use general application scenarios. General application scenarios initially describe supposed application possibilities of data mining that are likely to repeatedly occur in numerous organisations, by highlighting the general application area, the specific application purpose, the feasible mining methods, the (likely) needed data pool, and the expected kind of results. Referring to the above example figure 5 outlines a brief example of a general application scenario in turnover analysis.

General Application Scenario »Turnover Analysis«	
application area:	retention management
application purpose:	explaining and predicting voluntary turnover of (high performing) employees
data input:	employee master data, compensation data, development data, succession data, performance and appraisal data, ..., turnover data
method category:	classification analysis (static) association analysis sequential association analysis
kind of result:	(sequential) rules

Fig. 5. Example of a general application scenario.

So as to comprehensively evaluate data mining, diverse general application scenarios stemming for different functional areas such as staffing, appraising, developing and compensation are to be developed and evaluated. Additionally, so as to cope with the generalisation problem - an inherent difficulty of any action research approach - any application scenario should be iteratively evaluated in different organisations so as to validate the obtained evaluation results in different contexts and settings [15]. Positively evaluated application scenarios can be recommended to be practiced. This could be for instance offering (partially) predefined mining possibilities within future (business intelligence modules of) HRIS. Additionally, generalising from diverse positively as well as negatively evaluated application scenarios will distinctly contribute to scientific knowledge concerning the contribution of data mining to informate HRM.

In any case, data mining constitutes an analytical approach worth intensive future consideration in research as in practice.

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