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Process-oriented evaluation system for the use of robotic process automation

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Abstract

The administrative order processing is confronted with a variety of structural, procedural and organizational changes driven by the increasing demand for shorter delivery times and higher product variances. Thus, business processes become more complex and less transparent having a negative impact on administrative order processing. Studies estimate the waste in indirect areas at around 30 percent. The cause of this waste is, for example, missing information in the process step or interface losses during the transfer to another area of responsibility. This results in queries and coordination efforts that delay the order process. Among other things, robotic process automation (RPA) can be used to reduce waste. This enables the monitoring of administrative processes and the automation of sub-processes (activities). Identifying these automation potentials can be seen as a major challenge in administrative order processing due to the existing complexity. One way to discover automation potential is the use of data-driven tools such as process mining (PM). Using algorithms, a process model can be created on the basis of data from central information systems (e.g. enterprise resource systems), which enables a systematic analysis of causalities. Furthermore, PM can help to identify the relevant indicators for the suitability of the use of RPA in a data-driven way to decisively support the selection process. In the current state of research, most paper applying PM focus on quantifiable indicators for evaluating RPA capabilities. Qualitative criteria for RPA use are rarely considered.

This paper proposes on a qualitative criteria-based and quantitative indicator-based evaluation system for the use of RPA in administrative order processing, with the aim of eliminating waste in the sense of Lean Administration. The approach is validated in a PM software using a data set related to administrative order processing.

Keywords

business administration; lean administration; process mining; robotic process automation; evaluation system

1. Introduction

In recent decades, considerable potential has been leveraged in production by implementing the principles of the Toyota Production System as part of the Holistic Production System in manufacturing companies. These principles are increasingly being adapted to the indirect area as well, through so-called lean administration (LA). [1] Indirect areas are defined as areas which have a supporting function for the direct area, i.e. production, and are not directly involved in the physical production of goods. Examples of indirect areas are development, purchasing and sales. [2]

Administrative processes of indirect areas show significant differences to production processes. While raw materials and materials are processed in production processes, administrative processes generate data / information and intangible services that are far less visible and thus less traceable. Compared to production

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processes, these work contents are subject to high fluctuations in terms of the scope of work and the quality of information. Furthermore, administrative activities are less standardized and documented and therefore more difficult for employees to record. [3] Incidental tasks require flexible action, creative problem solving and a certain degree of freedom to make decisions [2]. As a result, the processing times in these process steps are highly variable. Nevertheless, they are essential for direct areas [4].

Less structured processes, a lack of transparency, a lack of process-related key performance indicators and a high coordination effort due to interdepartmental interfaces thus pose major challenges for the implementation of LA. Furthermore, LA methods are increasingly reaching their limits due to the dynamic environment and the existing complexity in administrative processes. An example of this is the process mapping through Makigami, which is very time-consuming and often only maps a small proportion of all possible process variants. Data-driven process modeling, in combination with the expert knowledge of employees, can compensate those disadvantages. In principle, synergies can be created on both sides by meshing the mindsets of LA and digital transformation. A study by SZEDLAK confirms this positive correlation between the two mindsets. For example, the study identified increased progress in LA among companies that have reached a high level of maturity in digitalization. Further, positive effects on corporate culture, leadership and collaboration were recognized. But also the process-oriented mindset promoted by LA was seen by the participating companies as a support for a sustainable introduction of digital tools. [5]

Despite all the challenges, administrative processes, as well as production processes, are to some extent repetitive, standardizable and measurable. Here, digital transformation tools can help to increase process transparency in order to systematically identify and specifically eliminate waste. In particular, PM and RPA have proven to be effective tools for identifying (through PM) and reducing (through RPA) waste in manual, repetitive activities. However, the identification of suitable processes poses major challenges for companies. Usually, the implementation of one of these technologies is understood as a stand-alone digitization solution. However, the combination of process and technology perspective can help to systematically identify and eliminate waste in administration. In the following, therefore, an approach is outlined which, taking into account the process-oriented mindset of the LA, should enable companies to make a targeted identification of administrative processes for the use of RPA.

2. Process mining and robotic process automation

2.1 Process mining

PM can be seen as a bridging discipline between the disciplines of Process Science and Data Science. The research field of Process Science includes disciplines of Business Process Management (BPM) or Operation Research (OR). These disciplines have a process-oriented character. In contrast, data-oriented approaches can be found in the research field of Data Science, including data mining, stochastics or visual analytics. The approaches of PM are especially related to those of Data Mining. In essence, three types of PM can be distinguished, which are briefly explained below [6, 7]:

- **Process discovery:** Process discovery uses an event log to generate a process model without using a-priori information. It is the most commonly used type of PM [8].
- **Conformance checking:** Conformance checking is characterized by comparing an already known process model with an event log of the same process. It is checked whether the process model corresponds to the reality (event log) or the reality (event log) corresponds to the model. The output generated here is diagnostic information about similarities and differences between the model and the event log.
- **Process enhancement:** In process enhancement (performance analysis), information about the actual recorded process from the event log is used to extend an existing process model and improve it if necessary.

In all types of PM, an event log is required as an input factor, which means that they have a crucial role. Especially in process discovery, the direct influence on the quality of the generated process model becomes clear. In essence, event logs provide information about the systemically recorded process steps. It is necessary that an event log contains at least information about the case, event and timestamp. To create realistic process models, a large number of cases is required. This is the only way to comprehensively map the complexity of the processes. For example, in the context of order processing, a case can be a unique order number. In this example, the events are activities such as order release, order completion, shipping, or invoicing. Accordingly, a case can contain a certain set of events. The timestamp provides a unique reference about the sequence of events. In addition to these minimum requirements, further information can be added to the event logs as attributes. [9,10,11]

With the help of algorithms, so-called miners, process models are generated in PM from the event logs, with the aim of showing the most accurate underlying model that is not invalidated by the next observations. [6] With the help of these process models and the knowledge of all process participants, administrative waste (e.g., process loops due to insufficient information or high inventories) can be identified and measures derived in a targeted manner. In this context, automation potentials can also be identified in order to use RPA.

2.2 Robotic process automation

According to the *Institute For Robotic Process Automation & Artificial Intelligence* (IRPAAI), the term RPA refers to a technological application “that allows employees in a company to configure computer software or a 'robot' to capture and interpret existing applications for processing a transaction, manipulating data, triggering responses and communicating with other digital systems.” [12]. The programmed “software robots” are capable of performing individual process steps in an automated manner. The software robot interacts with the IT systems involved in the process to imitate human user interaction in the process based on explicit if-then rules. In this process, data is extracted, manipulated and entered as input into other applications. Therefore, RPA can be seen as a non-invasive technical application that acts at the presentation layer. [13] An empirical study proves that the use of RPA entails low investment costs, short developing time, an increase in performance and a simultaneous reduction in costs and throughput time [32]. For this reason, RPA makes a wider range of processes lucrative for automation than traditional automation technologies [29].

Since RPA applications can interact with the user in the process and be triggered by certain actions, also partial process automation is enabled. Likewise, RPA applications can be used exclusively for process control, for example, to monitor incoming payments in finance and to improve process quality. In essence, software robots can be characterized as follows [14]: Software robots automate processes originally performed by humans, follow a choreography of technical modules and control flow operators and operate in an IT ecosystem and use existing applications.

3. State of the art

To identify the current state of research, a systematic literature research was conducted. In the process, the current literature databases were searched for existing approaches in the areas of “conventional criteria for identifying automation potential”, “data-based criteria for identifying automation potentials” as well as the “combination of PM and RPA”. After the initial screening, in summary 18 approaches were identified for detailed analysis. These approaches can be found in table 1.

Table 1: Identified approaches of the systematic literature research

Literature	Main focus
Category 1: Conventional criteria for automation potential	
[15] Fung 2014	Literature and interview-based discussion of criteria for the use of Information Technology Process Automation (ITPA)
[13] Smeets et al. 2019	Technical and business criteria for selecting the processes to be automated
[16] Beetz und Riedl 2019	Technical, business and organizational criteria for process selection
[17] Syed et al. 2020	Evaluation of existing literature to identify organizational and process criteria that indicate RPA maturity
[18] Langmann und Turi 2020	Minimum, additional and special criteria for the selection of RPA-suitable processes
[19] Eggert und Moulen 2020	Interview-based identification of practice-relevant criteria for the selection of business processes
[20] Plattfault et al. 2020	Interview-based identification of evaluation criteria for the suitability of a process for an RPA implementation
[21] Wellmann et al. 2020	Reference framework for the evaluation of RPA-suitable process characteristics
[22] Wanner et al. 2019	Multidimensional indicator system for quantifying the automation potential of a process
[23] Viehhauser und Doerr 2021	Identification and weighting of indicators to quantify the automation potential of a process
[24] Jeeva et al. 2021	Literature and interview-based identification of measurable criteria for process selection
Category 2: Data based criteria for automation potential	
[25] Leopold et al. 2018	Automatic recognition of the degree of automation of a process based on textual process descriptions using Natural Language Processing
[26] Van der Aa und Leopold 2021	Automatic recognition of automatable activities based on process models using Natural Language Processing
[24] Jeeva et al. 2021	Classification model for the selection of automatable processes
[27] Urabe et al. 2021	Clustering of user interface logs for the identification of task types and the respective workload as decision support for the selection of automatable processes
[28] Leno et al. 2021	Robotic process mining
Category 3: Combination of PM and RPA	
[29] Van der Aalst 2021	Identification of the interplay between process mining and RPA
[30] Schlund und Schmidt 2021	Challenges and future perspectives of RPA
[22] Wanner et al. 2019	Process mining as a basis for calculating quantitative indicators and optimizing economic benefits
[21] Wellmann et al. 2020	Application of the reference framework with the help of process mining for indicator-based determination of activities that can be automated
[31] Choi et al. 2021	Methodology for process selection by means of process mining

The analysis of existing approaches has shown that no generally valid criteria and indicators for identifying automation potential could be identified. Rather, there is great disagreement about which criteria and indicators are to be classified as relevant. Likewise, the granularity of the indicators and criteria shows great differences. Thus, according to some authors, the evaluation of indicators based on nominal or ordinal scales is sufficient, whereas other authors prefer a clear mathematical description. This reduces subjective influence in the context of scale-based evaluation by process experts. When analyzing the indicators, the differences in granularity also become clear. It can be seen that some of these are defined at the level of processes, subprocesses, or even activity level. Above all, it is striking that different approaches exist to define the same indicator, for example the degree of standardization. Furthermore, there is a lack of a holistic view of qualitative criteria and quantitative indicators. For example, information quality is not sufficiently considered in various approaches, despite its high importance for the application of PM.

This lack of general validity of the indicators and criteria makes it difficult for users to evaluate suitable processes in a targeted manner. In a study conducted by PLATTFAUT, for example, users describe the indicators and criteria available to date as, among other things, "too diffuse," "not differentiated enough," and "too intransparent" [22]. As a result, VAN DER AALST, among others, sees a need for further research in the identification of characteristics that describe the suitability of a process for an RPA deployment [29].

A catalog is therefore needed that adequately reflects the current state of research by combining qualitative criteria with quantitative indicators and categorizing them consistently as well as expanding them to include missing aspects. Even if this catalog will not establish general validity over the indicators and criteria, the user can thus fall back on a well-founded holistic tool. In addition to the PM and RPA specific criteria, the aspects of the LA must also be taken into account. This catalog of criteria and indicators is being developed as part of the evaluation system.

4. Development of the evaluation system

The process-oriented evaluation system for the use of RPA contains the catalog described above, including the qualitative criteria and quantitative indicators. The aim of the evaluation system is to provide the user with a defined order for identifying automation potentials in the indirect area, whereby certain degrees of freedom can be taken for individual use. In comparison to key figures, which in accordance with their merely descriptive function condense information and facts quantitatively in the form of a number, indicators do not describe directly measurable variables. Indicators therefore allow conclusions to be drawn about the characteristics and changes in complex processes. As a result, we will continue to refer to indicators. The developed evaluation system is described in detail below.

On the one hand, the event logs extracted from the IT systems (e.g. ERP systems) and, on the other hand, the expert knowledge of the process participants serve as input factors for the evaluation system (see figure 1). Quantitative indicators are determined from the event logs through the targeted use of PM, so that well-founded indicators based on the actual processes can be calculated and incorporated into the subsequent evaluation of RPA potential. This reduces the possibility of spurious accuracy compared to other approaches in the literature that consider purely qualitative criteria. However, as described above, the data quality of the event logs has a significant impact on the process model and thus also on the indicators. So qualitative criteria are added to the evaluation system. At this point, the expertise of the process owners is included. PM can support the process owners by increasing the process transparency through the visualization of the process model. Another advantage of including employee experience and expert knowledge is that the concept can also process information that is not interval-scaled or of high quality, as required, for example, by the approaches of VIEHHAUSER and DOERR, WELLMANN and CHOI (see table 1).

The previous approaches in the literature determine the qualitative criteria and quantitative indicators on the process or activity level. The latter is only pursued in the approaches of WANNER ET AL. and CHOI ET AL. They do not determine the automation potential for complete processes, but for individual activities independent of their process affiliation.

If the automation potential is only determined at the process level, there is a possibility that high or low automation potentials of the activities within the process compensate each other, which consequently leads to a low value of automation potentials for the entire process. Therefore, the determination of the automation potentials of individual activities proves to be advantageous. On the other hand, taking this perspective requires considerable time in practice. The evaluation system presented here takes advantage of both perspectives and therefore includes both the process and the activity level. To limit the analysis effort, a pre-selection of processes apparently suitable for the use of RPA is included. The criteria and indicators can already be consulted. The quantitative indicators are considered at the activity level, since a quick calculation can be made here through the PM. The qualitative criteria are first assessed at the process level in order to use employee experience to evaluate, among other things, higher-level impact relationships. After pre-selection by the quantitative indicators and qualitative criteria, qualitative criteria are used at the activity level to make a final process selection.

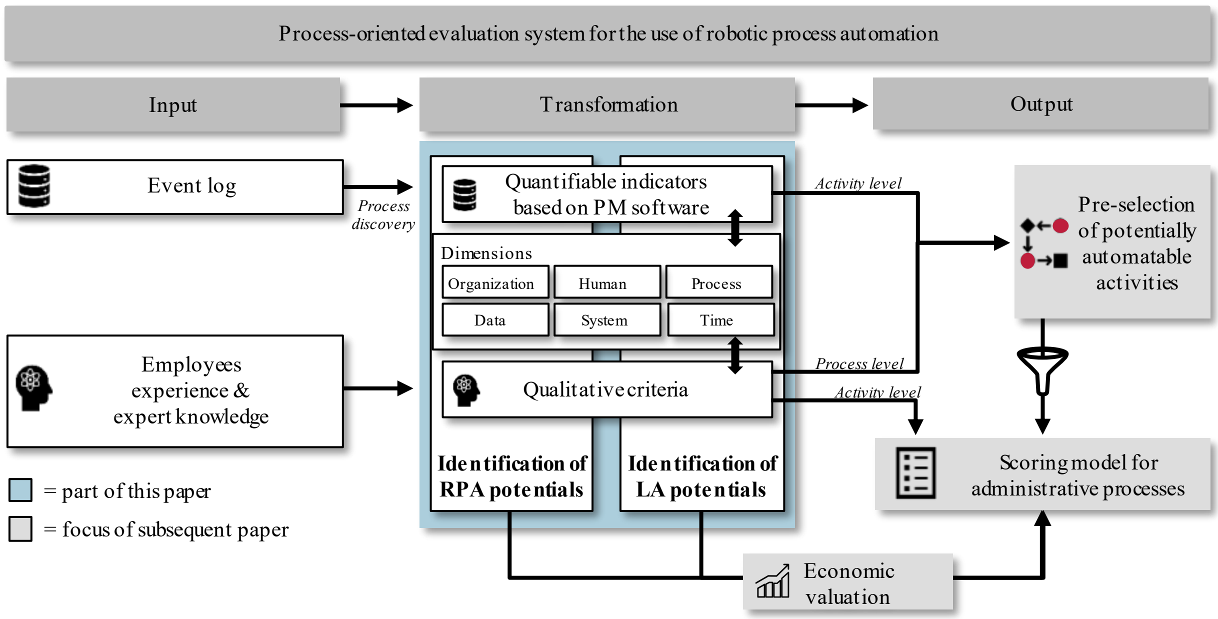

Figure 1: Process-oriented evaluation system for the use of RPA

The criteria and indicators integrated in the evaluation system can be classified into six dimensions (organization, human, process, data, system, time). These are used to determine the automation potential and to determine the LA potential. By determining both potentials, the scoring model prioritizes the ranking so that not only technology-specific requirements but also process-specific impacts on the implementation of LA are considered. In order to gain a better understanding of the structure and content of the criteria and indicators, they are presented in abbreviated form below.

5. Identification of RPA and LA potentials by means of criteria and indicators

The evaluation system is essentially based on two catalogs, which in turn contain assessment objects in the sense of criteria or indicators (see figure 2). If the approaches already discussed (see table 1) provide assessment objects, these are included in the catalogs. If no criteria or indicators are available in the literature for an assessment object, these are developed within the scope of this work. In some cases, qualitative criteria and quantitative indicators are available to the user for the evaluation.

Some assessment objects require a subjective evaluation and are therefore difficult to measure. For this reason, these are only included as criteria. Examples are the repetitive character of an activity, which is perceived by the executing employee, or the influences of automation on customer satisfaction, which are difficult or impossible to measure. [17,18] Here, in addition to the PM-based determination of the indicator, the user can determine the criteria, keeping subjective influences low to ensure objectivity. All criteria and indicators include a brief description and, in the case of the latter, a calculation specification as well. The notation used is based on WANNER ET AL. [22]

The determination of assessment objects with regard to LA potential is based on three building blocks. First, criteria and indicators from the literature were examined and implemented. For example, line efficiency or flow rate are classic lean indicators. [2] Further, criteria could be derived and integrated by analyzing the types of waste. In addition, the connection to the assessment objects of the automation potentials was investigated. Thus, the influences of the criteria and indicators on the LA potential were examined qualitatively. If an influence is suspected, the criteria or indicator is added to the catalog for determining the LA potential. For example, case frequency is included in this catalog because the higher the case frequency of a process, the higher the impact of eliminating waste in that process appears to be. This is also true for cycle time or processing time. Finally, all aspects of data quality are also included in the catalog, since it can be assumed in the course of the digital transformation that efficient process design is increasingly dependent on the quality of the data or information used.

The evaluation system provides for an individual selection of criteria and indicators. This offers the advantage of a situational adaptation to the decision problem at hand and to the associated framework conditions. However, the disadvantage is that individual selection counteracts the standardization and formalization of the decision-making process. For this reason, the freedom of choice is limited by a minimum selection per dimension, which is mandatory. If the possibility of recording exists, the indicator is to be preferred to the criteria even in the case of the minimum selection.

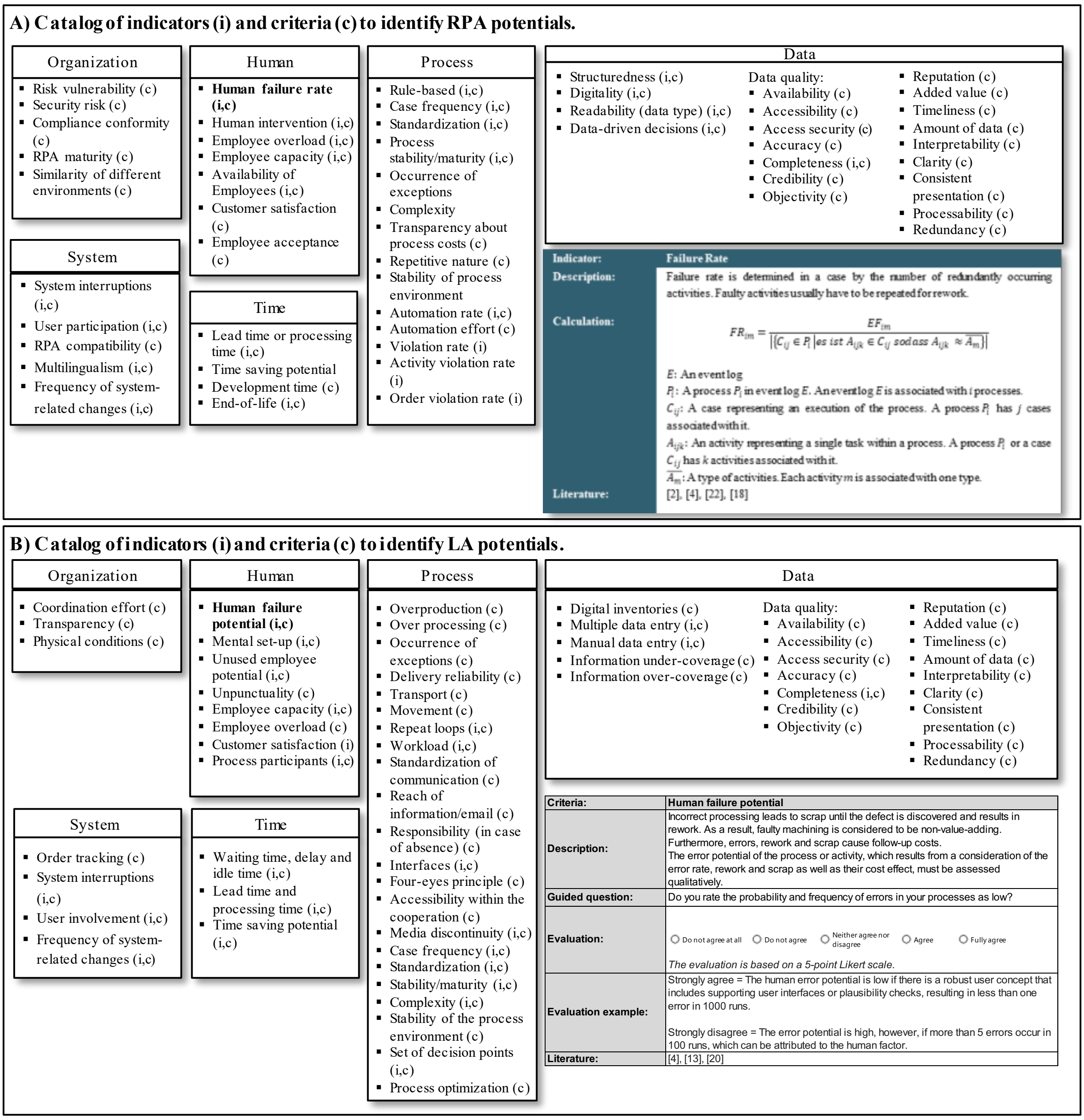

Figure 2: Catalog of indicators and criteria

6. Application, Validation and Outlook

The evaluation system is applied to an exemplary event log representing 1.12 million cases of a Purchase-to-Pay process (P2P) and 988 thousand cases of an Order-to-Cash process (O2C) provided by the PM software Celonis. The P2P process includes all activities to be performed from a good's procurement to the payment of the invoice, while the O2C process is its counterpart at the supplier's site. Since the preselection is trivial due to the given event log, a subset of criteria and indicators to identify the RPA and LA potential is formed based on the catalogs in a first step. This aims to address the most frequently mentioned RPA-criteria as well as all types of waste and to make maximum use of the event log. The extracted process models are then analyzed to determine the indicator values of each activity in Celonis.

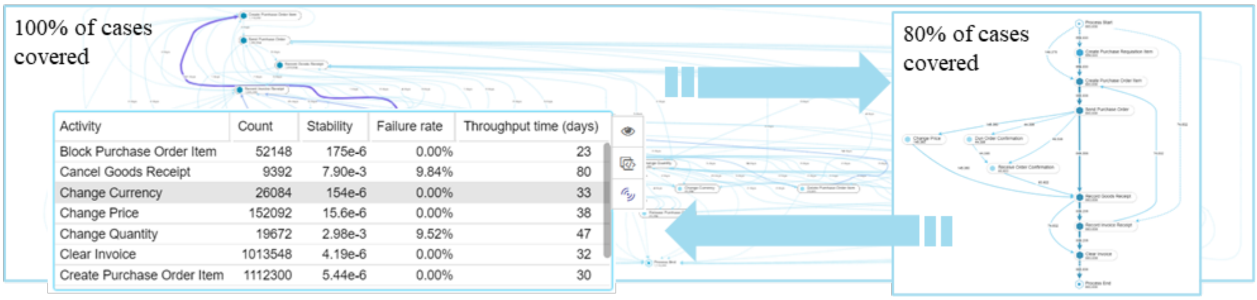

Figure 3: Indicator values of individual activities of the P2P process in Celonis

Due to the lack of deeper process-related knowledge, the criteria values of the activities are estimated on a scale from one to five regarding the respective context, where five is ideal. While the goods receipt, for example, seems to require frequent human intervention, sending an invoice appears to be more suitable for RPA. In terms of aggregation, a normalization and weighting of each criterion and indicator is needed. The lack of empirical knowledge about the ideal indicator values causes that these are normalized regarding the occurred minimum and maximum value. Criteria can be normalized based on the evaluation scale. To align the weighting with the objective of the RPA project, the objective dimensions "costs", "quality" and "time" are ranked and causal connections to the dimensions of the catalogs are qualitatively identified. Those criteria and indicators of the dimensions that are linked to the most important objective dimension are weighted three times higher than those linked to the least important one. This further allows to aggregate the criteria and indicator values to the RPA potential of each activity. The LA potential is calculated the same way, but at the process level. Based on the RPA potential, the decision whether an activity should be included in the partial automation of a process is made. The decision making might be supported by a threshold that in this case is estimated regarding the respective context. The RPA potential of the activities is then aggregated to the process level. The P2P process reaches an RPA potential of 54%, while the one of the O2C process is 69%. In addition, the LA potential of the P2P and O2C process are 58% and 49%. Visualizing the RPA potential, the LA potential and the results of an economic feasibility study, that is not shed light on in this paper, in a portfolio allows to determine the Euclidean distance of each process to the ideal value. Thus, the processes can be ranked and selected by averaging the three decision-making factors. Regarding the RPA and the LA potential only, a partial automation of the O2C process is recommended within the evaluation system application. Finally, a verification of the choice by examining the criteria and indicator values of the chosen activities allows to detect challenging criteria and indicator values that are compensated through the aggregation. For a first step of validation, the calculated RPA potential of each activity is compared to the recorded automation rate in Celonis, because it is assumed that an above-average automation rate correlates with a high actual RPA potential. The reproduction of the decision whether an activity should be automated using the automation rate shows that the calculated RPA potential is 88% in line with the automation rate. The evaluation system seems to be well suited to evaluate the RPA potential of a process.

All in all, this paper presents a process-oriented evaluation system that supports a more impartial multi criteria decision making using PM to identify the RPA and LA potential of administrative processes. The combination of qualitative criteria and quantitative indicators allows maximum use of the given process-related knowledge and event log. Although, the evaluation system needs to be further validated. Considering the catalogs of criteria and indicators future research opportunities arise. Empirical studies might support the determination of ideal indicator values. Moreover, the examination of their relevance and possible effects of multicollinearity might lead to a more sophisticated choice of criteria and indicators.

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Biography

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