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Process fit for RPA, feed back from field experts

L.L. Spoor

T.(Thijs) van Hest

Abstract
Robotic process automation (RPA) is seen as a high-impact solution – and perhaps even a hype – for many organisations that are struggling with inefficient business processes. However, the circumstances under which RPA is the best solution for optimising specific business processes are not always clear. It is generally recognised that data-quality demands and process characteristics are important factors driving decisions concerning whether to apply robotic automation to processes executed by humans. Assumptions about the importance of the characteristics and the influence on data quality are nevertheless part of the more tacit knowledge possessed by robotics consultants, builders and users. This tacit knowledge is however somewhat missing in current research literature. This field study is based on specific data about RPA implementation projects, as collected through interviews with several field experts. The results highlight the positive influence on data quality, as long as the input data are of sufficient quality and confirms, not surprisingly, existing knowledge about the relevance of certain process characteristics that should be considered when starting an RPA project. More specifically, the results indicate that some process characteristics (e.g., the degree to which processes are rule-based and the number of inconsistencies and uncertainties in a given process) are key factors driving decisions concerning whether to robotise specific business processes. Other process characteristics (e.g. process complexity) largely influence the design (and therefore the build time) of the robot, thus constituting key information in the business case for RPA. One set of process characteristics (e.g. process maturity and transaction volume handled by the robot) can provide input for determining the scalability of the robotic solution and the overall savings that could be achieved. Finally, the results highlight the importance of economic benefits, but also non-economic benefits of robotisation, including increased compliance or customer satisfaction.

Key words
Robotic process automation, Process characteristics, Process analysis, Data quality, Qualitative field study.

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I. INTRODUCTION

The ever-growing capabilities of technology significantly influence our workforce and the division of labour around the globe. A relatively new, albeit disruptive, technology involves the use of robotic process automation (RPA) to automate simple, rule-based, transactional processes.

RPA is however not the answer to all business process automation challenges. First of all, in some cases RPA continues to be inferior to back-end integration designed for machine-to-machine communication (Asatiani&Penttinen, 2016, Penttinen et al., 2018).

Penttinen et al. (2018), for example, categorise RPA as a lightweight IT solution that should be offset to the alternative of a heavyweight IT solution, like back-end system automation, in a given organisational context. For example, many organisations focus on the short-term economic benefits of RPA, while somewhat ignoring aspects related to governance (such as the sustainable utilisation of RPA) or more difficult measurable additional benefits (such as reduced compliance risk or increased customer satisfaction).According to van der Aalst et al. (2018) it is therefore necessary for researchers to devote more attention to the relationship between characteristics of processes andthe suitability of a process for robotisation. Secondly it is essential for any organisation to have confidence in the data produced by their robots, as the data will need to be consumed by downstream processes, be used for analysis, learning, control and reporting. As with other forms of IT, the implementation of RPA does not eliminate the need for change management activities (e.g. testing, training and governance). Despite the crucial importance of the relationship between the defined ‘proper optimisation’ of processes (as opposed to RPA characteristics) and the effect of RPA on data quality, little attention is given to this relationship (Syed et al., 2020; Santos et al., 2020). Thirdly, a lot of publications are derived from published case studies, without the comments of field experts (Osman, 2019).

This study is therefore mainly aimed at supplementing some practise knowledge regarding the relation of process characteristics, the decision to optimize a business process using RPA and data quality considerations. The results of this study could help affirm, underpin and enrich scholarly knowledge what is already assumed regarding the relationships(Bartunek and Rynes, 2014; van de Ven, 2018).

For the reasons discussed above, this study explores the following research question:
To what extent do RPA field experts recognize and acknowledge the relation between process characteristics, automation and data quality in assessing process fit for RPA?

Based on recent literature, we derived expectations regardingthe above-mentioned relationships.These were used to construct interview questions for the field experts, in order to provoke statements regarding the presence, the importance and direction of the relationship and assess the completeness of the recognized specific process characteristics addressed in the research question.

II. LITERATURE REVIEW AND DEVELOPMENT OF THE RESEARCH FRAMEWORK

In this section we will derive, based on academic literature, relations between process characteristics, automation and data quality that seem to be of importance in practise considering the use of RPA for optimization of a business process. These relations then, will be formulated in expectations, suitable for further research. Key words we used for finding relevant literature included automation, business process, data quality & robotic process automation.

Suitability criteria for selecting business processes for Robotic Process Automation

A business process can be defined as a collection of activities that combine different inputs to create an output that is of value to the customer (Hammer and Champy, 1993). Building from scratch as well as improving incrementally, for example with the use of RPA, can be a successful approach (Øvrelid E. and M.R. Halvorsen, 2019). Improvement of a business process can be prompted by economic reasons, but also by other, such as higher compliancy or customer satisfaction (Syed et al.,2020). These reasons are important general criteria for selecting a business process for RPA. RPA is a relatively new breed ofautomation software configured to emulate a human worker by interacting with information systemsthrough existing user interfaces (Institute for Robotic Process Automation, 2015; Lacity and Willcocks, 2016). Because the application of RPA assumes that a robot will replace a human, important criteria for the judgement will be whether the routines and affordances of the human can be transferred into the robot (Rutchi and Dibbern, 2020).

This fact explains why RPA is a popular solution especially aimed at improving data processingand, to a lesser extent, decision processes (Genpact, 2017). Especially in data intensive processes, which can be found in the financial services industry, the application of RPA is very popular (Genpact, 2017). Data are however also important in other, less data intensive, business processes. Data are used for communication within and over the business process aimed at the planning, execution, performance measurement, analysis and accounting of the process. This explains the close connection between RPA and accounting information systems as the latter are focussed on providing just that kind of information(Krishnan, 2005).

Assuming that the criteria are met regarding the transfer of the routines and affordances of the human into the robot, we can state that a robot has not, like a human, an incentive to present reality in a distorted way, it does not need a break and makes no mistakes due to fatigue or distraction. Based on this it can generally (Davenport and Short, 1990) be expected that the implementation of automation, such as RPA, in a process, leads to:

- higher demands on process standards (e.g. routines and affordances) and thus to;
- a higher consistency of the tasks performed and, thus, also to;
- higher quality of data.

More specifically, data are available at an earlier stageand are thus more relevant(Wang and Strong, 1996; FASB, 2008), not only for accounting purposes but for all kinds of tasks, such as analysis for performance management and decision support (Davenport and Short, 1990, Melchert et al, 2004). They are also more reliable due to the fact that the consistency, neutrality and verifiability rises (Maines and Wahlen, 2006) as a result of the fact that information transfer points, executed by humansare transferred to robots (Krishnan et al., 2005). We conclude therefore that the introduction of RPA in a business process contributes to a higher quality of data.

We conclude that the judgement regarding process fit for RPA depends on the following questions that could be answered through a business process analysis:

1. are the routines and affordances of human processing and decision taking activities in the business process such that they can be taken over by a robot?
2. Do the costs of building and managing the robot over time outweigh the savings on human labour and improvement of compliancy, customer satisfaction and data quality?

Judging business process characteristics

Based on the results of the literature review, we specify process characteristics that seems to be relevant considering the question whether a process is fit for RPA.They are presented in table 1.

	Process characteristic	Source
1.	Degree of process *standardisation*	Gruhn& Laue, 2017, Asatiani&Penttinen (2016), Slaby (2012), Seasongood (2016), Lacity et al., (2015), Romero et al. (2015), Willcocks et al. (2015), Fung (2014),Munstermann et al., 2009, Santos et al.(2020)
2.	Degree to which the process is *rule-based*	Asatiani&Penttinen (2016), Seasongood (2016), IRPA (2015), Lacity et al. (2015), Willcocks et al. (2015), Slaby (2012), Fung (2014), Santos et al.(2020)
3.	Degree of process *maturity*	Hammer, 2007, Kirchmer et al. (2017), Seasongood (2016), Lacity et al. (2015), Willcocks et al. (2015), Niehaves et al.(2014), Santos et al. (2020)
4.	Degree of process *complexity*	Gruhn& Laue (2017), Lacity et al. (2015), Willcocks et al. (2015), Fung (2014), Cardoso (2005), Slaby (2012), Santos et al. (2020).
5.	Degree of process *interdependence*	Gruhn& Laue (2017), Willcocks & Lacity (2016), Lacity et al. (2015), Willcocks et al. (2015)
6.	Transaction *volume*	Kirchmer et al. (2017), Asatiani&Penttinen (2016), Lacity & Willcocks (2016), Seasongood (2016), Slaby (2016), Willcocks et al. (2015), Fung (2014), Santos et al.(2020)

Table 1: Process characteristics related to RPA, as identified in existing research

In the following section, we will try to judge thecharacteristics with the help of the above mentioned suitability criteria.

I. *Degree of process standardisation*

Romero et al. (2015) define process standardisation as: "*Business process standardisation is the activity of unifying different variants of a family of business processes*". An element of the extent to which a process is *unified* (Romero et al., 2015) is the number of exceptions that occur when completing a task/process (Asatiani&Penttinen, 2016, Fung 2014, Slaby 2012): the higher the number of exceptions occurring within a process, the less standardised a process is. Exceptions in a process usually require human judgment that many RPA vendors do not offer today, which limits the automation potential of a process.

We conclude that the more a process is standardized, more information will be available regarding routines and affordances and thus a positive association is expected with the suitability of the process with the application of RPA.

II. *Degree to which the process is rule-based*

A rule-based process should not be confused with process complexity: both a very simple and very complex process can be highly rule-based. Asatiani&Penttinen (2016) make the need for rule-based processes specific as: "*currently RPA is suitable only for a particular type of processes that include only clearly defined, rule-based tasks, devoid of subjective human judgment*". Human judgment involves analysis, judgment, perceptual, or interpretive skills (Lacity et al., 2015).

Indicators of the degree to which a process is rule-based can be derived from the extent to which the process can be '*broken down into simple, straightforward, rule-based steps, with no space for ambiguity or misinterpretation*'and the extent to which all steps in the process can be precisely specified in writing, taking into account all possible events and outcomes along the way (Asatiani&Penttinen, 2016).

We conclude that the more a process is rule-based, the more the processing activities and decision activities can be automated and thus a positive association is expected with the suitability of the process with the application of RPA.

III. *Degree of process maturity*

The maturity of a business process, also referred to as process enablers, describe the capabilities of a process to function well over time, based on indicators such as comprehensiveness, abilities of the people (or robots) operating the process, process ownership, the match between requirements and design and process performance metrics (Hammer, 2007). These characteristics of an individual process are also expected to becaptured by other process characteristics, such as process standardisation and process complexity. The level of the organisation's business process management capabilities (Kirchmer et al., 2017),is expected to be related to the organisational readiness for RPA. These over-arching capabilities are likely to drive other process characteristics (e.g. the extent to which processes are standardised, documented and the description reflects reality (Seasongood, 2016)). Niehaves et al. (2014) argue, based on their research, that when determining the right level of BPM capability, contingency factors like environmental variables or organisational characteristics have to be taken into account.It could be argued that low-maturity organisations offer opportunities for RPA (e.g. manual, low

resourcing, static processes), but only in higher maturity organisations RPA could be deployed on a larger scale and an organisation-wide RPA capability could be built up in amore sustainable manner.
We conclude that the more mature a process is, routines and affordances of humans are better thought out and documented making the process a better candidate for RPA. We also conclude that this business process characteristic possibly overlaps with other business process characteristics.

IV. *Degree of process complexity*
Gruhn and Laue (2017) propose that there is no single measure for process complexity. Instead, there are a number of characteristics that jointly determine the complexity of a business process model. When viewing the process model as a flowchart or decision tree, elements that define complexity are: size of the model (Gruhn& Laue, 2007), control-flow complexity (Gruhn& Laue, 2017, Cardoso, 2005), cognitive weight of the model (Gruhn& Laue, 2017), structure of the model (Gruhn& Laue, 2017) and proneness to human manual error (Fung, 2014 and Slaby, 2012).
We conclude that the more complex a process is, the more difficult it presumably will be to understand and document the routines and affordances of the human processing and decision activities in the process. It will specifically influence the costs for building and management of the robot. All in all this will possibly result in a negative association between the process and the suitability of the process for RPA.

V. *Degree of process interdependence*
Within the scope of this research, *process interdependence* is described separately from *process complexity* as is often the case for RPA specific research (Lacity et al., 2015). An element of process interdependence that is crucial to RPA, (Lacity et al., 2015) is the extent to which the process has identifiable beginnings and endings. In other words the extent to which a process is integrated with and tightly coupled to other processes. Processes with a greater degree of interdependence are harder to robotise (Lacity et al., 2015). We conclude that the more a process is interdependent of other processes the influences of the other processes can and will rise the cost of management of the robotised parts of the process and thus make it a less logical candidate for RPA.

VI. *Transaction volume*
The quantities of data produced - the ‘transaction volume’ (Willcocks et al., 2015) - should be considered when implementing RPA, if only due to the simple fact that robots are able to process far larger quantities of data than humans in the same amount of time. Transaction volume can be seen as a different kind of process characteristic than the other process characteristics, as issues in data quality are not caused by the actual volume of the data, but increases in volume could amplify any (data quality) issues that find their origin in a process. When considering automation, processes with high volume of transactions create a more positive business case (Fung, 2014; Lacity & Willcocks, 2016), as greater run time will increase the potential savingsrealised by a robot.

We conclude that, generally, the application of RPA in a business process has a positive influence on data quality in a process. Process characteristics seem to be of major importance for the assessment whether a process is suitable for RPA, be it from the perspective of the possibility of programming the robot or the economic considerations on the short and long term. It also seems that some process characteristics interact with each other, such as process maturity, process standardisation and processes being rule based. We also conclude that it is possibly not easy to give a straightforward answer regarding the suitability of a process for RPA. It seems that specific information, not only about the process, but also about the organisation, is necessary to assess the opportunitiesto RPA.

The relationship between process characteristics, automation and data quality
Taken together, the characteristics presented throughout the previous section suggest the expectations shown in Table 2. These expectations concern the impact of the process characteristics (rows) on the suitability of a task for robotisation (second column) and on data quality (third and fourth columns).An arrow pointing upwards (↑) indicates a positive expected impact for a given process characteristic. A downward arrow (↓) indicates a negative expected impact on the suitability of a process for robotisation and on data quality.

		Suitability of the process for robotisation	**Data quality: A – Relevance**	**Data quality: B – Reliability**
1. Process standardisation		↑	↑	↑
2. Rule-based process		↑	↑	↑

3. Process maturity		↑	↑	↑
4. Process complexity		↓	↓	↓
5. Process interdependence		↓	↓	Neutral
6. Transaction volume		↑	↑	↑

Table 2: Expected impact of process characteristics

It is therefore interesting to find out how practitioners value the process characteristics with regard to the possibilities of RPA and the influence thereof on data quality. To challenge the practitioners, we choose to formulate the relations as straightforward as possible to find the nuance.

Expectations

Based on literature, we define two main expectations, each with six sub-expectations, one for each process characteristic. The expectations define the interview structure, serve as a framework for the interview themes and define the coding table that is used to structure the analysis of the data gathered in the interviews.

Nr	Expectation
1.	**Each of the six process characteristics has an effect, either positive or negative, on how successful a robot will be in executing a specific process, as compared to a human.**
1.1	An increase in the degree of *process standardisation (1)* will have a positive effect on the suitability of that process for robotic automation.
1.2	An increase in the degree to which a *process is rule-based (2)* will have a positive effect on the suitability of that process for robotic automation.
1.3	An increase in the degree of *process maturity (3)* will have a positive effect on the suitability of that process for robotic automation.
1.4	An increase in the degree of *process complexity (4)* will have a negative effect on the suitability of that process for robotic automation.
1.5	An increase in the degree of *process interdependence (5)* will have a negative effect on the suitability of that process for robotic automation.
1.6	An increase in *transaction volume (6)* will have a positive effect on the suitability of that process for robotic automation.
2.	**Depending on the process characteristics, the outputs of a robot executing a process differ in terms of data quality (relevance and/or reliability), as compared to the outputs of a human executing that process.**
2.1	As the degree of *process standardisation (1)* increases, a robot will increasingly produce better data quality in terms of relevance (A) and reliability (B), as compared to a human.
2.2	As the degree to which a *process is rule-based (2)* increases, a robot will increasingly produce better data quality in terms of relevance (A) and reliability (B), as compared to a human.
2.3	As the degree of *process maturity (3)* increases, a robot will increasingly produce better data quality in terms of relevance (A) and reliability (B), as compared to a human.
2.4	As the degree of *process complexity (4)* increases, a human will increasingly produce better data quality in terms of relevance (A) and reliability (B), as compared to a robot.
2.5	As the degree of *process interdependence (5)* increases, a human will increasingly produce better data quality in terms of relevance (A) and reliability (B), as compared to a robot.
2.6	As the *transaction volume (6)* increases, a robot will increasingly produce better data quality in terms of relevance (A) and reliability (B), as compared to a human.

Table 3: Research expectations and sub-expectations

III. RESEARCH METHOD

Introduction

To pursue our research goal, we consider it important to gather information from multiple sources in multiple contexts, maintaining an open mind as to what occurs in practice, given the rapid evolution of the research topic in response to technological advancements (Stebbins, 2001). Because the process characteristics and their relationship with data quality and fitness for robotisation are partly still open for interpretation and discussion we did not define the relations in a specific measurable way. New insight from practitioners regarding components as well as relations can be typified as qualitative data and therefore best be obtained by qualitative research interviews (Kvale, 1983). They provide a suitable research method for gathering such data. Ideally, the participants should be practitioners and experts in the field of RPA -for example as consultants, developers or users - thereby ensuring the consideration of various facets of the phenomenon.

Instrumentalization: creating the interview guide

As stated above, the causal relationships between the variables addressed in this research are partly known. To challenge the existing views, we formulated expectations and used them in the topic list as a starting point for our conversations with experts, with the aim of ensuring completeness in the discussion of all process characteristics and dimensions of data quality. The same structure was applied during every interview, in order to ensure comparability. The participants were informed by email about the research goal. The lead questions on the relevant topics in the interviews are presented in Appendix A. The structure of the interviews is presented in Table 4.

Section	Description	Purpose
1 *5 min*	Introduction, agenda/structure of the interview, explanation of the goals of the study.	To align expectations and agenda between interviewee and interviewer.
2 *40 min*	Walkthrough of each of the expectations and insights concerning the relationships between process characteristics, RPA and data quality; active search for real-life examples.	To gather information about relationships between variables.
3 *10 min*	Additional information, ensuring room for additional cases or examples, ensuring complete data collection if new cases/examples are brought up in line with research structure.	To ensure completeness of variables and outcomes, and to enrich data collection to the greatest extent possible.
4 *5 min*	Explain subsequent steps, express gratitude for participation.	To conclude the interview and to manage expectations about subsequent steps.

Table 4: Interview structure

The interviews could be classified as realist interviews, as all participants were encouraged to share their personal, daily experiences with RPA as consultants, developers or users (King, 2004, 2, p.12).

Participants

As stated above, our preferred participants were experts or individuals with significant experience in the field of RPA, and specifically with hands-on experience in robotising and/or improving previously non-robotised processes. An additional selection criterion was that these experts had experience with at least one (and preferably more) successful and at least one (and preferably more) unsuccessful robotised processes in terms of the data quality of the outputs. This criterion was intended to ensure that the participants could relate to both robotised and non-robotised processes. The fact that participants fulfil different roles with respect to RPA asserts that the analysis gains in validity by increasing the number of different viewpoints collected via interviews(King, 2004, 2,p.16).

The direct and indirect network of one of the researchers was used to select and approach the preferred interviewees. In time, 11 were willing to participate. A description of the characteristics of the interviewees is included in table 5 below, the metadata are provided in Appendix E. After the initial interview, the research setup was evaluated, to ensure it proved to function well for this method of data collection.

Nr	Code	Function
1.	C1	Consultant (Manager) Technology (RPA) - the Netherlands
2.	C2	Consultant (Senior Manager) Finance (RPA) - the Netherlands
3.	B3	RPA consultant &developer - the Netherlands
4.	B4	RPA developer - the Netherlands
5.	B5	RPA consultant &developer - the Netherlands
6.	B6	RPA consultant &developer - the Netherlands
7.	C7	Consultant (Senior Manager) Technology (RPA) – Switzerland
8.	C8	Consultant (Director) Technology (RPA) Switzerland & Singapore
9.	C9	Consultant (Partner) Technology (RPA) - the Netherlands

10.	U10	Process improvement manager Financial Shared Services Centre in airline industry – Bulgaria
11.	U11	Global Product Owner RPA / digital internal consultant airline industry - the Netherlands

Table 5: Research participants list

Data processing

The interviews were conducted during February and March 2019. Allinterviews were recorded, transcribed in MS Word and coded for purposes of data analysis according to the method of thematic text analysis (King,2004, 21, p.256). The coding was executed according to a coding table that had been derived from the expectations(Appendix B).

After each interview, the transcript was validated with the participant, thereby enhancing the quality of the data by validation and reducing researcher bias (Slagmulder, 1977). The interview transcripts and code lists were imported into ATLAS.ti for analysis. After each interview, the research structure was validated for completeness based on new insights derived from each interview.

Data analysis

The main technique used to analyse the data is most commonly referred to as pattern matching (Hak&Dul, 2009, Yin, 2018). This technique allows for the assessment and analysis of expected and unexpected patterns, thereby generating deep insights into topics of interest in the research. The ATLAS.ti software package was used for the processing, analysis and interpretation of the data. This tool, which is classified as 'computer assisted qualitative data analysis software' (CAQDAS), is useful for processing large quantities of qualitative data. After the standard coding list had been uploaded into ATLAS.ti, the software package was used to code the interviews. Differences between the groups of participants were examined as part of the analysis.

To ensure that the data is analysed in a structured manner, the code frequency, code co-occurrence, and codes-primary document tables in ATLAS.ti are used to examine the relative importance of particular themes (i.e., how frequently they are mentioned), as well as how they are related to each other and to the themes and qualifications formulated in the expectations (as described in table 3). In this study, ATLAS.ti is used as a tool for highlighting important statements and experiences in the source text regarding the existence and power of relationships that are relevant to this research. This study thus combines techniques of interpretative phenomenological analysis (IPA) and template analysis. A study based solely on template analysis should preferably involve 20 to 30 participants (King, 2004, 21, p.257). Most qualitative research, however, sets a premium on diversity because it seeks to show the range of ways that a phenomenon is experienced within the chosen context. This study is not solely based on template analysis. We think that using the expectations in all interviews, comparing the results and deepening out new topics of interest will assure that importantfeatures will be reaffirmed and not be missed, especially thanks to the diversity of the participants. Creswell suggests that participants in phenomenological studies could range from 6 – 25 (Creswell, 1998).

Data is captured, using the expectations as a framework, and labelled with unique codes. The coding table used is included in Appendix B. The coding process allowed for an in-depth analysis of the associations between all variables. The code-frequency table is included in Appendix C, and the co-occurrence table is included in Appendix D.[1]

To ensure confidentiality, each interviewee is assigned a number from 1 to 11, indicating the number of the interview, and a letter, indicating the participant's role within robotic process automation: a robotics user (U), an external developer (B) or a consultant (C). Additional details of the interviews and interviewees are provided in Appendix F. Text fragments are identified by a combination of the letter and interview number, followed by a dash and a number referring to a specific section of text in the interview transcripts. For example, C1-1 refers to Interview 1, with a Consultant, in Text section 1.

Descriptive statistics are derived from the frequency and co-occurrence of codes. The code-frequency analysis provides an indication of the importance or weight of specific codes. Although it is useful as an initial exploration of all codes, it does not indicate any relationships between them. The code co-occurrence analysis provides insight into aspects including the interactions between different codes by analysing the extent to which the codes co-occur in segments of the interview.

An initial exploration is conducted based on the most and least used codes. The codes are arranged into three

[1]The raw interview data will be made available only on request.

groups: 1) Process characteristics, 2) Suitability for robotisation, 3) Data quality.

The code co-occurrence analysis is conducted by generating a code co-occurrence table using ATLAS.ti (see Appendix B). The software package generates co-occurrence ratios for all codes, as calculated with the following formula: C12=n12/(n1+ n2–n12). The co-occurrence ratio (C) indicates the strength of the association between coded sections of text: a higher co-occurrence ratio (C) indicates a stronger association. In all tables, stronger associations are indicated by a darker shade of green.
For the initial code co-occurrence analysis, only the general process characteristic codes (110, 120, 130, 140, 150, 160, 170) were used, with no indication of direction (i.e. only a high, medium or low degree of each process characteristic). This analysis reveals the overall relationship.

Validity and reliability of the study
Although the use of a topic list and statements based on theory enhances the validity and comparability of the research findings, these features could also cause the conclusions to be one-sided. For this reason, during the interviews, participants were challenged to critically analyse the hypothesised relationships and to mention other aspects that might be of interest. Finally, all participants were experienced in the field of RPA.
The use of ATLAS.ti increased both the reliability and the validity of the study through the creation of visible audit trails.

IV. RESULTS

The results include the answers provided by the experts involved with respect to the expectations, which were derived from theory. First, *descriptive statistics* were used to conduct a broad exploration of the data with respect to the two main expectations, followed by a *detailed analysis* of the data with respect to the 12 sub-expectations.

Expectation 1: Each of the six process characteristics has an effect, either positive or negative, on how successful a robot will be in executing a specific process, as compared to a human.

All process characteristics are associated to some extent with the suitability of the process for robotisation. This result provides support for Expectation 1. With low ratios (0.02 - 0.06), however, the associations of four process characteristics (standardisation, maturity, complexity and transaction volume) are significantly lower than those of the other process characteristics.

Expectation 2: Depending on the process characteristic, the outputs of a robot executing a process differ in terms of data quality (relevance and/or reliability), as compared to the outputs of a human executing that process.

All process characteristics are associated with a positive effect on both the relevance and the reliability of data. None of the process characteristics are associated with the absence of a significant impact on data quality. These results suggest that the performance of a robot has a positive influence on data quality, as compared to the performance of a human, except in cases involving complex processes (0.13) and data inputs that are of poor quality (0.10).

		Suitability of the process for robotisation	**Data quality: A – Relevance**	**Data quality: B – Reliability**
1. Process standardisation	Expected Found	↑ ↑	↑ ↑	↑ ↑
2. Rule-based process	Expected Found	↑ ↑	↑ ↑	↑ ↑
3. Process maturity	Expected Found	↑ ↑	↑ ↑	↑ ↑
4. Process complexity	Expected Found	↓ ↑	↓ ↑	↓ ↑
5. Process interdependence	Expected Found	↓ ↑	↓ ↑	↓ ↑

6. Transaction volume	Expected Found	↑ ↑	↑ ↑	↑ ↑
7. Quality input data	Expected Found	NA ↑	NA ↑	NA ↑

Table 6: Results

Detailed results

In this section, we provide additional details on specific relationships between the individual process characteristics, including their impact on 1) the suitability of a process for robotisation and 2) the relevance and reliability of data. The discussion is enriched by contextual information, quotations and insight gained during the interviews. We also analyse the interactions between process characteristics and the interaction between the two dimensions of data quality.

Effect of process characteristics on robotisation and data quality

Degree of process standardisation (1)

As noted above, the results of the first stage of the analysis indicate the existence of relatively strong positive (0.17) and negative (0.14) associations between the degree of process standardisation and the suitability of a process for robotisation. The direction in which this association occurs is in line with expectations derived from literature. The results therefore provide support for Sub-expectation 1.1.

An important explanation revealed during the interviews is that '*standardisation has a positive impact on the potential to robotise, because the fewer exceptions there are, the better a process can be robotised*' (B3-1) and '*the fewer the variations there are in a process, the better a robot will be able to deal with all situations*' (B6-1). In various interviews (C2, B4, B5, C7), the participants described the standard process, including its known exceptions, as the 'happy flow'. The known exceptions are also related to Sub-expectations 2.1 and 2.2: the degree to which the process and its exceptions are rule-based. Exceptions can be divided into business exceptions and system exceptions (C8-1), and a robot should be capable of handling both business and system exceptions (C8-1). Business exceptions are those that are part of the business process, and system exceptions are '*basically anything related to the system that the robot is affecting and that has a problem*' *(C8-1)* (e.g., a crash in Microsoft Excel, which is a usual suspect for RPA). Robots are usually very well equipped to handle system exceptions (C8-1), as long as those system exceptions are part of the robotised process. For example, the robot will need to know how to handle system crashes in order to safeguard data quality for both relevance (A) and reliability (B) (e.g., to prevent duplicate data when re-starting a process after a crash). Although any robot must be built in such a way that it can address both business and system exceptions, each type of exception must be addressed in a different way in order to prevent data-quality issues.

Another reason why process standardisation has a positive impact on the suitability of a process for robotisation is its scalability: '*So, if I have a process that is highly standardised, that means to me that the process probably operates in the same way everywhere it's done. So, let's say you have a finance process in a global company. It's very standardised. It operates the same way in Switzerland, in the US, in Holland and in Singapore. Standardised means that they do exactly the same thing, the exceptions are the same and the way they're handled is the same. To me, however, that doesn't say anything about the complexity of automating the process. So, I would argue, that high standardisation helps with scaling, because, if you build the robot in Switzerland and you can copy-paste the same kind of robot to all of your other countries, this can help you to scale*' (C7-1). Process standardisation '*is certainly an important and helpful indicator, but, to me, it would be more relevant if I'm talking about scale then if I'm talking about the yes/no in terms of automation*' (C7-2). As illustrated by these quotations, process standardisation is interpreted in different ways. In some cases, it focuses on the number of exceptions and the 'happy flow' while, in others, it provides input for determining the scalability of a solution for a global company. The relative scalability of solutions is important to the RPA business case and roadmap.

An important enhancement to the understanding of this relationship was provided by Respondent C8, who explained the very low association ratio (0.01) between a moderately standardised process and one that is suitable for RPA, emphasising that '*if the process is highly standardised, I would say that it had already been automated, albeit through an IT interface*' (C8-8). In many cases, highly standardised processes that handle large volumes of data have already been automated by the organisation at an earlier stage (C2-5). The business processes for which RPA is a proper solution constitute an important point, which is addressed further in the discussion.

The results also show that the degree of process standardisation has a positive impact on the relevance and reliability of data. An important benefit of using a robot – in terms of both the relevance and the reliability of data – is that the robot is rule-based by definition (B4, C7), and it never loses focus or becomes tired (B5, B6, C7). The robot is thus capable of performing exactly the same task over and over again, and at a faster pace than a human could. '*Yes, it's simple, right? A robot doesn't have a hangover on Friday because it went out Thursday night*' (C7-5).

Degree to which the process is rule-based (2)

The degree to which a process is rule-based is very clearly related to its suitability for robotic automation. A highly rule-based process is strongly associated (0.28) with a positive effect on robotisation, while those that are not very rule-based (code 121_Degree to which the process is rule-based_low) are strongly associated (0.30) with a negative effect on robotisation. These results are in line with the expectations based on theory. All participants identified the degree to which a process is rule-based as being highly important when executing a process analysis to determine which processes are suitable for RPA: '*absolutely critical. If you're talking about pure-play RPA, then it's absolutely critical*' (C7-4). Some of the interviewees also stipulated that it is sometimes difficult to determine the degree to which a process is truly rule-based: '*Strangely enough, my experience is that people often think that they're making great judgments, but if you really talk them through the process and you start to break it down, you realise that most of the judgment is not really based on judgment at all, but on rules. But I think that this [being rule-based] is absolutely a key factor*' (C7-3). Although cognitive judgment is often seen as a limiting factor, multiple participants (C2, B4, C7, C8, C9) indicated that they often encounter scenarios in which 'cognitive judgment' is really nothing more than a series of rules or a '*multi-layer decision tree*' (C9-3).

The relationship between the degree to which a process is rule-based and elements of judgment or subjectivity also became apparent when exploring data quality. The degree to which a process is rule-based exhibits a similar relationship, in which a highly rule-based process is associated with a positive impact on data quality (A 0.13, B 0.15) and a process that is rule-based only to a low degree (code 121_Degree to which the process is rule-based_low) is associated with a negative impact on data quality (A 0.21, B 0.22).

Degree of process maturity (3)

As stipulated above, a lower degree of process maturity is strongly associated with a negative effect on the suitability of a process for RPA (0,23). A similar pattern can be found in the relationship between a low degree of process maturity and a negative effect on data quality (A 0.24, B 0.27). A possible explanation for this relationship could be that process maturity is an overarching process characteristic with an indirect impact on one specific business process. For this reason, when process maturity is low, it can be an indication of other issues that lead to a negative association with processes that are not suitable for RPA. For example, a low degree of process maturity is strongly associated with a low degree of process standardisation (0.28), but it is also associated with a high degree of process complexity (0.11).One respondent offered an example involving a current client, in which '*it is so fragmented, so immature, that we cannot achieve a positive business case*' (C2, 8:8). Both process maturity and process standardisation seem to influence the scalability of RPA (C7-1). This helps to explain the strong association between a low degree of process maturity and a low degree of process standardisation (0.28).

A high degree of process maturity can also lead to (or be an indicator of) a higher degree of process complexity, although this relationship is not necessarily reflected in the associations: '*I think greater maturity is probably related to greater complexity. Because, if you have an isolated task that is fairly simple to do, and its rule-based, it is an easy case. For more mature and end-to-end processes, with data truly flowing from the end back through your entire process, you will certainly have more dependencies and your complexity will certainly increase*' (C7-6). Based on the input received, it seems quite plausible that process maturity interacts with other process characteristics (e.g. standardisation, complexity and interdependence), although it is not directly related to the suitability of any specific process for robotisation or to the quality of the data. At the same time, however, process maturity also appears to be an important process characteristic to consider in terms of the organisation's readiness for RPA, as well as its scalability and the RPA business case.

Indirectly, process maturity should have a positive effect on data quality in terms of both relevance and reliability: '*because I would argue that, if you have a complex process, with high maturity, which also increases complexity, but you have a robot to run it through and you have the robot use the right data, I think it would probably be beneficial to the data quality from an end-to-end process perspective. If you do the same thing with a human, I'm not sure if that would still be the case, because the human would have to handle more data and carry it through the entire process (remember more steps)*' (C7-7). This remark describes a positive impact of process complexity on data quality. This unexpected observation is discussed in the next section. In addition, '*Automation may help you to become mature*' (U11-19), as increased visibility of issues relating to automation or data resulting from RPA might inspire the owners or operators of business processes to reach out beyond their functional silos to see how upstream processes could benefit from certain improvements (U11-19).

Organisations with a higher degree of process maturity might offer more opportunities for scaling robotic automation, '*but organisations with a lower degree of process maturity could possess more "low-hanging fruit"*' for robotic automation (U11-15).

Degree of process complexity (4)

The degree of process complexity reveals a very interesting relationship, involving both a strong association with a positive impact (0.20) and an association with a negative impact (0.04) on the suitability of a process for RPA. This relationship could be explained by the existence of multiple interpretations of complexity within the boundaries of RPA. For example, one interpretation concerns the size of the model (Gruhn& Laue, 2017) or decision tree that contains the rules within a process. In this case, process complexity would have a positive impact (0.20) on the suitability of a process for robotisation. This relationship is especially (or perhaps even exclusively) applicable to processes that are highly rule-based, as robots are better than humans capable of proceeding through very large but consistent decision trees (C2-4, B5-4, C7-9): '*Especially with complexity, that is where humans make the most errors. Yes, also in rule-based processes, because they are so boring, but mostly in terms of complexity*' (C2-4). As clearly stated by another respondent: '*Well, I would love to let this [high degree of process complexity] be done by a robot. I believe that, as long as the process is consistent, the more complex, the better it would be to let a robot do it*' (C11-8).The theoretical expectation is based on more classic business process management theory. They do not consider the specific drivers underlying processes that are suitable for robotic automation, but are aimed at broader process-management decisions, mostly with regard to processes executed by humans. The direction of the relationship is determined by the definition of complexity: '*So, for me, complexity is less of an issue. We have developed processes that are highly complex in terms of a certain number of steps and tasks, connected to a certain number of many systems. If you use the number of systems, number of steps or number of decision trees in a process as a proxy of complexity, I see this as less important. The level of uncertainty is more important. For example, if the stakeholder for a process were to say, "I'm actually not 100% sure what I would do as a next step", it would largely depend on a judgment call or on how the process would operate today - a different exception every day. Even if it is a very short, five-step process, I would not recommend RPA. If the process involves someone reading an email, interpreting the content of the email and deciding what to do next, this might be just a two-step, single-system process: 1) read the email, 2) decide what to do next. I would not go with RPA, because this process requires too much cognitive ability from a human*' C8-6). Although processes that require human judgment can be regarded as complex from the perspective of a robot, they indicate that a process is rule-based to only a low degree. In addition, complexity is often remedied by breaking up highly complex processes (i.e., processes with large decision trees) into smaller components (B4-7, B5-10) that are easier to build. A higher degree of process standardisation (the modularisation of the model: Gruhn& Laue, 2017; Lacity et al., 2015; Fung, 2014) and being rule-based to a high degree could help to accomplish this.

The association between the degree of process complexity and data quality is also reversed as compared to our theoretical expectations. Based on theory, we expected to find a negative relationship between process complexity and robotisation. The data nevertheless suggest a positive relationship between process complexity and both the relevance (0.19) and the reliability (0.21) of data. These outcomes suggest that a higher degree of process complexity increases the suitability of a process for RPA and improves the data quality of the robot, as compared to a human, as long as the preconditions (highly rule-based processes) are met.

Degree of process interdependence (5)

The relationship between the degree of process interdependence and the suitability of a process for robotic automation and its impact on data quality resembles that of process complexity. Although we expected to observe a negative association, the results show a positive association when the pre-conditions are met. A high degree of process interdependence is associated (0.16) with a positive impact on the suitability of a process for RPA. Interestingly, however, it is also associated (0.11) with having a negative impact on the suitability of a process for RPA. The explanation for this relationship is that, as the number of interdependencies increases, this effectively increases the size of the model or decision tree. As such, process interdependence is essentially a sub-variable of process complexity. According to many participants, this is a common practice in process analysis, in which the number of distinct inputs and outputs of a process is used as input for the complexity of the process (C1, C7, C8). As the number of interdependencies increases, however, the extent to which the requirements of those interdependencies change over time also increases. Changes in the requirements of the interdependencies (e.g., a change in the report template made by an external user of data provided by a robot) require the robot to change: '*I would say that, if it is always the same [rule-based and stable], it [process interdependence] is a bit like [process] complexity. Once you have built it in a certain way and it is stable, a robot will be better at dealing with all of these [interdependent and/or complex] things. As long as nothing changes, a robot will definitely be better at handling them. And I think that, unfortunately, in the real world,* *things change more often than we would like*' (C7-15). '*If the interdependencies are defined consistently, a robot would be better at dealing with them than a human would be*' (B6-16). Changing requirements require thorough change management and governance of the robot, in order to safeguard the quality of the data. If these safeguards are in place, or if the requirements of the interdependencies are not very likely to change often, process interdependence will be associated with a positive effect on both the relevance (0.19) and the reliability (0.18) of data. A high degree of process interdependence is associated with a positive impact on the relevance (0.15) and reliability (0.14) of data.

Transaction volume (6)
Higher transaction volumeis associated with a positive impact on the suitability of a process for robotisation (0.12), as well as with a positive impact on data quality (A 0.15, B 0.13). The results also reveal a slight association between low transaction volume and a positive impact on the suitability of a process for robotisation (0.01), as well as with a positive influence on data quality (A 0.02, B 0.02). Although transaction volume is often used as input for the business case of RPA (C1, C2, B3, B5, B6, C7, C8, U10), this is an indication that robots can also be deployed to run business processes resulting in benefits other than those that are purely economic (B5-9). '*But this CFO actually indicates, "I just want people to enjoy their work and perform value-added activities. Whether the business case is positive or not is really none of my concern*"' (B5-6). Respondent C7 offered the example of how robots are utilised to mitigate risks for financial institutions in Switzerland. This example, however, is related to one of the qualities of a robot: its ability to handle large quantities of data: '*A Swiss bank is an important client, for whom much work has been done in the field of risk and compliance. This is because, after optimising the process, they can now cover 100% of the transactions. In the past, they had employed people to perform a spot checks and sample checks, testing only a fraction of the cases. Since the process was optimised, these people have been able to focus on exceptions and truly hard cases, while the robots essentially test all of the cases*' (C7-11).
Another important advantage of robots is that they automatically log secondary (C9-1) data about the process (B3-8, B6-2, C7-17). '*We are currently working hard to log process data, for example, for process mining or AI* [Artificial Intelligence]. *When a process generates more data, we can know more about the process, and this provides an excellent opportunity for further optimising the process*' (B3-8).

Data quality of inputs (7)
We had no separate theoretical background or expectations for the data quality of inputs, as this perspective was captured in process interdependence in the form of 'fan-in, fan-out' metrics (Gruhn& Laue, 2017). The first interview of the series (C1) brought up the *data quality of inputs* as a separate variable; separate from the degree of process interdependence. This view was specifically tested and confirmed by most other participants. The reason for including the variable separately it is based on the 'garbage in/garbage out' (C1) principle: when the data quality of the inputs in a process are of higher quality, this helps to enhance the data quality of the outputs.
A high degree of data quality of inputs is associated with a positive impact (0.07) on the suitability of a process for robotisation. A low degree of data quality of inputs is also associated with a negative impact (0.13) on the suitability of a process for robotisation. We observed a similar relationship for the impact of the data quality of inputs on the data quality of outputs, with a high degree of data quality of inputs being positively associated with the relevance (0.09) and reliability (0.09) of data. A low degree of data quality of inputs is negatively associated with the relevance (0.17) and reliability (0.33) of data. If the data quality of inputs is poor, "*the human might think "okay, this isn't working, maybe there is an extra letter in the contract number that I can replace". The human thus has room to play around. Robots don't do that. If a robot doesn't recognise the contract number, it will throw it out as an error. At the end of the day, if the robot produces an error, the human will have to come in and fix it. If the human was already doing it, this would save that little bit of time*' (C1-5).
Another way to operationalise the data quality of inputs could be to determine whether the input is based on a template, thus implying a more rule-based manner of input (B6-25). A possibility for mitigating poor data quality being used by a robot could be to build in pre-validation of the data (C1-12, B6-20) according to a set of rules (e.g. expected values). Similar to the comments concerning transaction volume (6), this could help to optimise processes and improve the data quality of interdependent (5) processes.

Interaction between process characteristics
The interaction between process maturity and the other process characteristics has already been specifically addressed in light of the insights derived from the interviews. Nevertheless, other process characteristics interact as well. This is important input for the analysis and selection of processes for RPA projects within any company.
The strongest interactions between process characteristics were observed between the degree to which processes are rule-based on the one hand, and process standardisation (0.21) and process complexity (0.19) on the other

hand. When asked what their first question is in determining whether a process is suitable for robotisation, without going into the business case, many participants identified the extent to which the process is rule-based as the first (C1, C2, B3, B4, B5) or one of the first (B6, C7) questions that they ask or analyse. There was also a relatively strong association between process standardisation and process complexity (0.10). Looking solely at the technical possibilities of RPA, the participants regarded process standardisation (1), the extent to which a process is rule-based (2) and process complexity (3) as very important. Process maturity was strongly associated with process standardisation (0.19). This could be explained in terms of the scalability of RPA in highly standardised processes within organisations that exhibit a high degree of process maturity.

Interaction between processes that are suitable for RPA and data quality

To ensure the completeness of the results across all possible relationships, participants were also asked to describe the association between variables describing the extent to which processes are suitable for RPA (201, 211, 221) and data quality (301-303, 311-313).

The results reveal a strong association in both directions: processes identified as suitable for RPA show a positive effect on data quality (A 0.43, B 0.44) while processes identified as not suitable for RPA show a negative effect on data quality (A 0.32, B 0.35).

In most of the interviews, the participants noted (C1, C2, B3, B6, C7, C8, C9, U11) that the direct relationship between process characteristics and data quality is often not explicitly considered in RPA projects, although it is definitely important. This observation is supported by the associations found, as the results clearly demonstrate that processes that are positively associated with RPA due to a positive fit with RPA through a set of process characteristics also have a positive effect on both the relevance and reliability of data.

Interaction between the dimensions of data quality

In most cases, only slight associations were found between specific process characteristics and the relevance and reliability of data. The only stronger associations that differentiate the relevance (A) and reliability (B) of data as outputs were observed when the data quality of inputs is low. This relationship was explained in the preceding section.

Differences between groups of participants

A difference between the groups of participants is worth noting: Consultants (C) and robotics users (U) were more broadly oriented than developers (B) were towards improving business issues by considering technological issues other than RPA as well. The absence of other significant differences between groups of participants indicates that the research results can be generalised to a greater degree than would have been the case if greater differences had been observed between the groups.

V. DISCUSSION

Process characteristics and the suitabilityfor RPA

Theory (Sayed et al, 2020) suggests a negative relationship between process complexity, process interdependence and the suitability of a process for robotisation. According to our results, however, this relationship is reversed andfound positive in practice. This suggests that there are more possible cases for robotisation than often taken into account.When it comes to RPA, process complexity appearsto be driven by (1) the extent to which a process is rule-based and involves cognitive judgment or cognitive components, (2) the number of exceptions in the process (process standardisation) and (3) process interdependence or distinct inputs and outputs of the process. Increasing process complexity along the above three drivers of complexity is not necessarily an issue for a robot, as long as the process can be fully mapped on a consistent decision tree(C1, C2, B4, C7, C8, C9). Increased size and complexity of the decision tree usually leads to a longer build time for the robot, increasing costs and negativelyaffecting the business case (B6), but a robot is far better at dealing with such a large, consistent but complex decision tree than a human is. Comparable to building with LEGO bricks, the increased building time due to process complexity is often mitigated by breaking up a large and complex process into smaller bricks (B4-7, B5-10) that are easier and less expensive to build, but also better to maintain. Similar logic is applied when automating parts of an end-to-end process that are highly suitable for robotisation, instead of automating the entire process (U10, U11), which is usually much more difficult and expensive (if possible at all), this process is robotised in smaller components or bricks.

Transaction volume is often seen as a key factor in RPA (Sayed et al, 2020; Osman, 2019; Kirchmer et al., 2017; Asatiani&Penttinen, 2016; Lacity & Willcocks, 2016; Seasongood, 2016; Slaby, 2016; Willcocks et al., 2015; Fung, 2014). It is interesting to note that transaction volume, as suggested by Lacity and Willcocks (2016), was not perceived as a driver of process complexity for RPA (C1, C2, B3, B5, B6, C7) as it does not change the way a business process is robotised, it is mostly a driver of required capacity of the robots and poses a specific challenge such as additional required controls, to cope with larger numbers of data.

A relationship could be expected between high transaction volume and process standardisation (C8), since a process managing highertransaction volume is likely to be optimised and standardised by an organisation from a cost saving and quality perspective. Our results, however, do not indicate a strong association (C=0.03) between transaction volume and process standardisation as it comes to RPA. This finding might be a result of how transaction volume is oftentreated in RPA process analysis: not as a decisive factor in determining the technical suitability of a process for robotic automation but as a driver of the return on investment. A robot that handles more data and therefore usually requires more capacityis more interesting from a business-case perspective (C1, C2, B3, B5, B6, C7), due to the greater potential for cost savings (B5-6), as compared to lower transaction volume processes. Another advantage of robots is their ease of scaling up capacity (U10-18, U11-13) when operating processes involving foreseen and unforeseen peaks or seasonality.

An important advantage of process standardisation that is not fully captured in theory (Syed, 2020) is the extent to which a robotised process can be scaled to other areas of the organisation (C7-1, C7-2). In addition to increasing the scalability of RPA, this aspect makes it more interesting from a business-case perspective. The degree of process standardisation is related to the degree of process maturity, as emphasised by the strong association between the degree of process standardisation and the degree of process maturity (0.19). Distinguishing between the maturity of specific process enablers and organisation wide business process management maturity (e.g. Hammer, 2007) could prove to be very useful input to an organisation that considers RPA. The maturity of an individual process defines, in conjunction with the other process characteristics as described throughout this study and proven significant, how suitable an individual process is for robotic automation and enriches the set of process characteristics with more governance related topics such as process ownership.The maturity of business process management of an organisation is expected to be much more related to the overall company's strategy with regards to RPA and could therefore drive true adoption of RPA throughout the organisation instead of deploying RPA to a single business process. The maturity of business process management could therefore have a far greater impact on the organisation when it comes to RPA(Syed, 2020), but only when certain conditions to individual business processes are met, which are defined by this research.

This poses challenges to the organisational governance of RPA. One of the benefits of RPA is that it is relatively easy to automate a business process, as a robot essentially mimics human behaviour on a computer (Asatiani&Penttinen, 2016). Humans execute no longer the business process as is the case with heavy-weight IT (Rutschi and Dibbern, 2020)The benefit of the relatively low-barrier entrance to RPA is also a risk: how do you as an organisation control for the quality of your data, especially as it relates to interdependent (fan-out) processes outside of the business function building the robots. It also poses challenges to the quality of a robot being built, in order to safeguard the outcomes or the data produced by the robot. These governance questions to RPA, are quite new, but essential when rolling out RPA on a larger scale. And, as RPA can quickly grow to a large scale and become scattered in an organisation that shows signs of a low enterprise wide business process management capability, it is vital for these organisations to form a vision towards RPA early on: how to combine lightweight IT (RPA) with heavyweight IT (true business process and system integration) into the optimal mix that fits the organisation's characteristics and maturity.

Process characteristics, automation and data quality

Based on the results of this study the relationship between process characteristics, robotic automation and data quality is strongly positive. This benefit was not yet explicitly highlighted in theory (Syed et al, 2020, Osman, 2019) When a process is suitable for robotic automation the effect on dataquality for both the relevance and reliability is positive, given that a specific set of conditions is met: a business process should be highly rule-based, predictable and stable. If that is the case, also a highly complex process, or a business process with a large number of interdependent processesthat are stable, a robot will produce better data quality than a human operating that same business process. Data handled by a robot are more consistently processedand timelier available (relevance of data). Because the robot always follows a rule-based script, the reliability of the throughput and output of a process are more reliable than of a process handled by humans, given the data quality of the input of the process is also of sufficient data quality.

The data quality of inputs (7) was added as a seventh process characteristic, and most of the interviewees (C1, C2, B5, B6, C7) explicitly considered it an important process characteristic. For other participants (C7, C8), this aspect was captured in the concept of process interdependence. However, process interdependence describes the number of distinct inputs and outputs (C7), and not the data quality of those distinct inputs. This process characteristic is relevant, given the importance of ensuring that a robot has high-quality data at the start of the process in order to execute its rules (garbage in/garbage out).

Surprisingly this research did not reveal the specific influence robotisation has on the management of information systems as a whole. Data quality is not only influenced by the application controls on the operational levels of the business process but also by controls related to systems development, change management, datasecurity and business continuity activities on higher organisational levels (Weber et al, 2009).

One could argue that these issues are taken care in mature processes by using business process management capabilities. These capabilities foresee, for example, whether the application of lightweight IT, such as RPA, is really an advantage for the organisation as a whole or that the change of heavyweight IT is a more sustainable solution (Kirchmer, 2017).

VI. CONCLUSIONS, RECOMMENDATIONS AND LIMITATIONS

Conclusions

In line with theory and existing research, the results of our study confirm that all identified process characteristics are relevant when performing feasibility studies concerning selecting processes for robotic automation, but with different levels of significance and/or priority. Some process characteristics are more important or fundamental to the success of business process robotisation than others. Another important overall finding is that some process characteristics are subject to different interpretations and applications, such as the degree of process standardisation, process complexity and process maturity, whereas other process characteristics, such as the degree to which a process is rule-based, are more consistently defined and applied.

The influence of some process characteristics on the suitability of a business process for robotisation, suchas the extent to which a process is rule-based and standardised, has been well known for some time. The influence of some other characteristics, such as process maturity or the role of process complexity,has been less clear or often interpreted incorrectly. This study provides a comprehensive overview of whether and how process characteristics influences the ability to automate these processes through RPA and the expected effect robotisation will have on data quality.

The results clearly reveal the impact of RPA on data quality. For processes that are suitable, robotic automation is expected to have a strong positive impact on both the relevance and reliability of data. The fact that data are faster, in more detail and free from human bias, available, should be taken into account as a major contribution to business judgement and monitoring purposes. For processes that are not suitable, robotic automation is expected to have a negative impact on data quality, mainly as a result of the so called ‘fan in’ and ‘fan out’ condition. Even though data quality is not always explicitly considered when implementing RPA, careful process selection and automation remains essential in order to safeguard data quality. We believe this quality can not only be guaranteed at the process level, but the effect of robotic automation should also be consideredon an organisational level. An important question to be answered with respect to RPA is, for example, whether the development and change management of the business process itself and/or the scripts the bots use are entrusted at the process level, top level or within an IT-department.

In the next paragraph we like to present some guidelines, based on our research, relating toprocess-selectionin preparation for the implementation of RPA.

Recommendations

Guidelines for process selection and defining the business case for RPA

In this paragraph, based on the findings of this research, we derive some specific guidelines with respect to the assessment whether aprocesscould be suitable for RPA. Such an assessment is part of the so-calleddynamic road map for RPA implementation (Sigurðardóttir, G.L., 2018) As such this assessment is part of the RPA Conceptual model presented by Santos et al (2020).As the roadmap presented in earlier research is somewhat general our findings provide some specific advice regarding optimization of a business process.

General guidelines

First of all, we conclude that the optimization should be motivated and rationalized from the strategic perspective of the business involved. This could result in useful criteria to evaluate the expected contribution of the optimization efforts, be it with or without RPA. The improvement of data quality should be taken into account explicitly. This also involves the evaluation of process ownership and accountability regarding business process results.

Next, we believe it is important to avoid misinterpretation among all involved regarding the explicit meaning of some characteristics of a process, such as complexity, maturity, interdependency, standardisation. Such misunderstanding can lead to missing potential for improvement.

We suggest using some practical measures, such as basic low, medium, high indication or a percentage between 0% and 100% to indicate whether (parts of) a process is (are) standardised.

Specific guidelines regarding optimization with RPA

Step 1The extent to which a process is rule-based is often seen as a starting point when assessing RPA suitability of a process (C1, C2, B3, B4, B5, C7, C9). Most interviewees indicated that assessing the extent to which a process is rule-based and the extent to which it is devoid of human judgment (Rutschiand Dibbern, 2020; Asatiani&Penttinen, 2016) is the first step in estimating whether a process is fit or suitable for RPA (C1, C2, B3, B4, B5, C7, C9). If a process is not sufficiently rule-based and/or contains significant components of human judgment (e.g., analysis, judgment, perceptual or interpretive skills; (Rutschi and Dibbern, 2020; Lacity et al., 2015), process optimisation is required in order to increase the degree to which a process is rule-based, and therefore suitable for RPA. In some cases, however, the number of judgments in a business process and therefore the degree to which a process is rule based was found difficult to determine. A step in a process which is perceived as cognitive judgment is often actually a consecutive series of rules or a '*multi-layer decision tree*' (C9-3) and can have excellent possibilities for robotisation as long as all steps in the process can be precisely specified in writing, taking into account all possible events and outcomes along the way (Rutschi and Dibbern, 2020; Asatiani&Penttinen, 2016). A very low degree to which a process is rule-based could immediately lead to process de-selection for RPA, at which point process redesign should first be considered before moving forward with robotising the specific business process.

Step 2After a process has been confirmed as being highly rule based, the number of exceptions (a key element of degree of process standardisation: Asatiani & Penttinen, 2016, Willcocks et al., 2015, Lacity et al., 2015, Fung, 2014, Slaby, 2012) and the degree of process interdependence could be investigated in parallel.
The degree of standardisation provides an indication of the number of exceptions in a process. The processes that are most suitable for RPA are those with only a limited number of exceptions or a limited need to handle exceptions (Asatiani & Penttinen, 2016; Fung 2014). A distinction is made between business and system exceptions, and the expectation to which these business and system exceptions are known and predictable, as this means the exceptions could be configured in the robot's decision tree. Higher numbers of exceptions do not necessarily pose problems, as long as those exceptions can be handled in a rule-based manner (Fung, 2014; C2, B4, B5, C7). Process descriptions need to be much more explicit for robots than for humans (Rutschi and Dibbern, 2020; Lacity et al., 2015).
The degree of process interdependence addresses the number of distinct inputs and outputs. The data quality of those inputs and the frequency of significant change of inputs and outputs can be drivers for process de-selection, as this increases complexity of the business process.

Step 3The degree to which a process is rule-based, the number of known business and system exceptions and the process interdependence are input to estimate the process complexity: the size of the model (Gruhn & Laue, 2007), the structure of the model and the control flow complexity (Gruhn & Laue, 2017, Cardoso, 2005). These three drivers together determine the cognitive weight of the model, which is an indicator of the degree of process complexity (Gruhn & Laue 2017, Fung 2014, Slaby 2012).
Lastly, the accessibility of the applications the robot will require to operate the business process requires investigation. Application accessibility is about the ease with which a robot is able to use the required applications and is influenced by for example whether the solution resides in the cloud or on premise, the ease of logging in, the frequency of changes to the application (U11-16).
At this point, a separation could be made between processes that are selected and deselected for robotic automation *from a technical build perspective*.

Step 4As a follow-up, input could be gathered about the degree of process standardisation in terms of organisational scalability, the degree of process maturity, the number of transaction volumes and possible additional benefits due to robotic automation (e.g., a reduced level of compliance risks, or increased customer satisfaction. Together, this allows users to define a structured business case and roadmap for RPA, *from a process characteristics perspective*. Likely, other information to complete the business case is required, such as the savings potential in FTEs (Full Time Equivalents). As part of the roadmap, considerations described in this research could be considered: the systems architectural considerations, the organisation readiness for RPA and the careful selection of the RPA developer.
Overall, it becomes very clear that implementing robotic automation is very much about removing any inconsistencies or unexpected events from a business process before deploying a robot to execute that specific process.

Overall, this research will help answer fundamental questions such as what '*the workforce of the future*' may look like, in which humans and robots will increasingly co-exist and need to work together. This future may be closer than we think. Society in general and organisations in particular will need to identify the best fit within their workforces to combine human and virtual employees in an efficient, responsible and sustainable manner, to continue to realise their competitive edge.

Limitations

This research is of an exploratory nature, and it is based on a relatively small sample of qualitative data. This is

partly remediated by selecting a diverse group of participants to ensure a broader range of experience and input. However, future research performed at a larger scale or a longer period could provide additional insights or deeper insights in the relationships identified.
Secondly, only a limited body of theory is available on the relationship between robotisation and data quality. To our knowledge, our study is the first to assess the relationship between process characteristics, data quality and the feasibility of RPA from a process perspective.
All observations discussed above are based on the current capabilities of RPA software, which are continuously evolving. The integration of artificial intelligence (AI) and cognitive automation components into RPA tools is making them even more powerful, as it allows robots to start handling unplanned situations and dealing with unstructured data (Kirchmer, 2017). This will change the relationship between some of the elements involved in this research, including the relationship between process characteristics, the suitability of processes for RPA and the expected effect on data quality. For example, the extent to which a process is rule-based will likely become less important for robots that are increasingly endowed with machine-learning capabilities (C1, C2).

Future research
Future research is needed in order to test and enrich the guidelines in daily practice. The guidelines allow for specific and controlled data collection on all variables and relationships. These guidelines can be used to develop a step-by-step process selection model for RPA, taking into account all process-and environmental-related considerations, including the required quality of data, the fit of RPA for an organisation and the business case. Such a model is expected to be a useful tool in daily business practice.
Secondly, in the future, research could be devoted to the organisational implications of deploying robots on a larger scale, how this relates to organisational- and IT governance, the optimal mix for any organisation between lightweight and heavyweight IT and the relationship between business process management maturity. We expect that an organisation will need to form such a vision early on in order to prevent scattered growth of RPA across organisation in pursuit of cost savings, but in parallel crippling the organisation capabilities to organise along end-to-end processes and respond appropriate to changing conditions.
A third category of recommended future research concerns the manner in which future developments in AI and machine learning will impact the research outcomes. The increasing capabilities of robots could be expected to generate continuous changes in this relationship, thus implying continuous changes in the ways in which organisations should utilise RPA. Although the degree to which processes are rule-based is currently a key factor, it could become less important in the near future as robots become better equipped to handle decisions requiring cognitive skills and as their capabilities come increasingly closer to those of humans. The latter development means also that more attention should be given to privacy and ethical concerns (Tauli T., 2020, p.316).

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Appendix A: Interview questions

Nr	Question
1	Research introduction, expectations, timing.
2	**Based on the cases you have seen, how would you indicate how each process characteristic is related to the technical (or other) suitability of a business process for robotic automation?**
2.1	[Short explanation of process characteristic] Degree of process standardisation?
2.2	[Short explanation of process characteristic] Degree to which the process is rule-based?
2.3	[Short explanation of process characteristic] Degree of process maturity?
2.4	[Short explanation of process characteristic] Degree of process complexity?
2.5	[Short explanation of process characteristic] Degree of process interdependence?
2.5	[Short explanation of process characteristic] Transaction volume
3	**Considering the cases for robotics [successful or unsuccessful] that you have seen in terms of data quality of outputs, how would you estimate the direct effects and impact [yes/no] that each process characteristic has on the six dimensions of data quality?**
2.1	Process standardisation [for each dimension of data quality, indicate 1) no impact / 2) positive impact / 3) negative impact + room for specific comments]
2.2	The degree to which the process is rule-based [for each dimension of data quality, indicate 1) no impact / 2) positive impact / 3) negative impact + room for specific comments]
2.3	Process maturity [for each dimension of data quality, indicate 1) no impact / 2) positive impact / 3) negative impact + room for specific comments]
2.4	Process complexity [for each dimension of data quality, indicate 1) no impact / 2) positive impact / 3) negative impact + room for specific comments]
2.5	Process interdependence [for each dimension of data quality, indicate 1) no impact / 2) positive impact / 3) negative impact + room for specific comments]
2.6	Transaction volume [for each dimension of data quality, indicate 1) no impact / 2) positive impact / 3) negative impact + room for specific comments]
3.	**In which order would you investigate these process characteristics and any other factors that determine the suitability of a process for robotic automation within the context of business or at the start of a project involving RPA?**
4.	**Closing**

Appendix B: Transcript coding table

Codename Level 1	Codename Level 2	Codename Level 3	Sources
1_Process characteristic	11_Degree of process standardisation	110_Degree of process standardisation	Asatiani&Penttinen (2016), Slaby (2016), Lacity et al., 2015, Romero et al. (2015), Willcocks et al. (2015), Fung (2014), Munstermann et al. (2009)
		111_Process standardisation_**Low**	
		112_Process standardisation_**Med**	
		113_Process standardisation_**High**	
	12_Degree to	120_Degree to which the process is rule-based	Asatiani&Penttinen (2016), Seasongood

	which the process is rule-based	121_Degree to which the process is rule-based_**Low**	(2016), IRPA (2015), Lacity et al. (2015), Willcocks et al. (2015), Slaby (2012), Fung (2014)
		122_Degree to which the process is rule-based_**Med**	
		123_Degree to which the process is rule-based_**High**	
	13_Degree of process maturity	130_Degree of process maturity	Kirchmer et al. (2017), Seasongood (2016), Lacity et al. (2015), Willcocks et al. (2015), Fisher (2005)
		131_Degree of process maturity_**Low**	
		132_Degree of process maturity_**Med**	
		13_Degree of process maturity3_**High**	
	14_Degree of process complexity	140_Degree of process complexity	Gruhn& Laue (2017), Lacity et al. (2015), Willcocks et al. (2015), Fung (2014), Cardoso (2005), Slaby (2012).
		1410_Degree of process complexity_**Low**	
		1420_Degree of process complexity_**Med**	
		140_Degree of process complexity_**High**	
	15_Degree of process interdependence	150_Degree of process interdependence	Gruhn& Laue (2017), Willcocks & Lacity (2016), Lacity et al. (2015), Willcocks et al. (2015)
		151_Degree of process interdependence_**Low**	
		152_Degree of process interdependence_**Med**	
		153_Degree of process interdependence_**High**	
	16_Transaction volume	160_Ttransaction volume	Kirchmer et al. (2017), Asatiani&Penttinen (2016), Lacity & Willcocks (2016), Seasongood (2016), Slaby (2016), Willcocks et al. (2015), Fung (2014)
		161_Transaction volume_**Low**	
		162_Transaction volume_**Med**	
		163_Transaction volume_**High**	
	17_Degree of data quality of inputs	170_Degree of DQ of inputs	Derived as relevant codes from pilot interview. Often captured as part of process interdependence: Gruhn& Laue (2017)
		170_Degree of DQ of inputs_**Low**	
		170_Degree of DQ of inputs_**Med**	
		170_Degree of DQ of inputs_**High**	
2_Process suitable for RPA	20_Process suitable for RPA_positive	201_Process suitable for RPA_**Positive**	
	21_Process suitable for RPA_no sign diff	21_Process suitable for RPA_**No sign diff**	

	22_Process suitable for RPA_negative	22_Process suitable for RPA_**Negative**	
3_Data Quality	30_DQ_relevance	301_DQ_relevance_**Positive**	Laudon & Laudon (2016)
		302_DQ_relevance_**No sign diff**	
		303_DQ_relevance_**Negative**	
	31_DQ_reliability	301_DQ_reliability_**Positive**	Laudon & Laudon (2016)
		302_DQ_reliability_**No sign diff**	
		303_DQ_reliability_**Negative**	
4_Other benefits	40_other benefits	400_other benefits	N/A - used to tag other benefits of RPA in relation to process characteristics or dimensions of data quality.

Appendix C: Code frequency table

	C1	C2	B3	B4	B5	B6	C7	C8	C9	U10	U11	Totals
110_Degree of process standardisation	15	4	3	3	5	5	4	6	0	3	3	**51**
111_Process standardisation_low	6	1	0	0	0	0	1	1	0	2	1	**12**
112_Process standardisation_med	0	0	0	0	0	0	0	1	0	0	0	**1**
113_Process standardisation_high	6	3	3	3	3	2	1	1	0	2	2	**26**
120_Degree of process rule based	9	7	3	4	3	4	8	4	2	4	4	**52**
121_Process rule based_low	2	1	0	0	1	0	1	0	0	2	0	**7**
122_Process rule based_med	0	0	0	0	0	0	0	0	0	0	0	**0**
123_Process rule based_high	6	5	3	3	1	2	5	2	2	2	4	**35**
130_Degree of process maturity	8	5	2	1	1	1	3	2	0	2	0	**25**
131_Process maturity_low	5	3	0	0	0	0	2	0	0	1	0	**11**
132_Process maturity_med	2	0	0	0	0	0	0	1	0	1	0	**4**
133_Process maturity_high	2	1	2	1	1	1	0	0	0	0	1	**9**
140_Degree of process complexity	6	5	4	3	3	2	4	3	1	4	1	**36**
141_Process complexity_low	1	1	0	0	0	0	0	0	1	1	0	**4**
142_Process complexity_med	0	0	0	0	0	0	0	0	0	0	0	**0**
143_Process complexity_high	5	3	4	3	2	0	2	3	0	4	1	**27**
150_Degree of process interdependence	5	1	3	1	1	1	5	1	1	2	2	**23**
151_Process interdependence_low	0	0	0	0	0	0	0	0	1	0	0	**1**
152_Process interdependence_med	0	0	0	0	0	0	0	0	0	0	0	**0**
153_Process interdependence_high	2	1	3	1	1	1	3	1	0	2	3	**18**
160_Transaction volume	2	7	4	1	1	1	4	1	2	2	5	**30**
161_Transaction volume_low	0	3	0	0	0	0	0	0	0	0	0	**3**
162_Transaction volume_med	0	0	0	0	0	0	0	0	0	0	0	**0**
163_Transaction volume_high	0	3	4	1	1	1	3	1	1	2	5	**22**
170_Degree of DQ of inputs	3	1	2	1	0	1	4	0	0	0	1	**13**
171_DQ of input_low	1	1	1	0	0	0	1	0	0	0	0	**4**
172_DQ of input_med	0	0	0	0	0	0	0	0	0	0	0	**0**
173_DQ of input_high	2	0	1	1	0	1	1	0	0	0	1	**7**
201_Suitable for RPA_positive	10	13	9	9	3	4	8	8	5	7	7	**83**
211_Suitable for RPA_no sign dif	1	0	3	0	0	0	1	0	0	1	2	**8**

221_Suitable for RPA_negative	8	4	2	0	2	0	3	1	0	3	0	**23**
301_DQ relevance_positive	7	10	10	5	4	2	5	3	2	2	3	**53**
302_DQ relevance_no sign dif	0	0	0	0	0	0	0	0	0	0	0	**0**
303_DQ relevance_negative	5	1	0	0	1	0	2	0	0	1	0	**10**
311_DQ reliability_positive	7	10	10	4	4	2	6	3	2	5	2	**55**
312_DQ reliability_no sign dif	0	0	0	0	0	0	0	0	0	0	0	**0**
313_DQ reliability_negative	5	1	0	0	1	0	1	0	0	0	0	**8**
400 Other benefits	0	6	2	1	3	1	4	4	2	2	3	**28**
Totals	**131**	**101**	**78**	**46**	**42**	**32**	**82**	**47**	**22**	**57**	**51**	**689**

Average # used	**18,1**
Average per interview	**86,1**

Appendix D: Code co-occurrence table

Code co-occurrence overall	Process characteristics																			
	110_Degree of process standardisation	111_Process standardisation_low	112_Process standardisation_med	113_Process standardisation_high	120_Degree of process rule based	121_Process rule based_low	122_Process rule based_med	123_Process rule based_high	130_Degree of process maturity	131_Process maturity_low	132_Process maturity_med	133_Process maturity_high	140_Degree of process complexity	141_Process complexity_low	142_Process complexity_med	143_Process complexity_high	150_Degree of process interdependence	151_Process interdependence_low	152_Process interdependence_med	153_Process interdependence_high
110_Degree of process standardisation		0,24	0,02	0,57	0,21	0,05		0,1	0,19	0,09	0,06	0,05	0,1	0,04		0,05	0,01			
111_Process standardisation_low	0,24				0,05	0,19			0,16	0,28		0,05	0,02							
112_Process standardisation_med	0,02																			
113_Process standardisation_high	0,57				0,1			0,13	0,11		0,11	0,06	0,03	0,03		0,06				
120_Degree of process rule based	0,21	0,05		0,1		0,13		0,78	0,1	0,02	0,06	0,02	0,19	0,04		0,14	0,04			0,03
121_Process rule based_low	0,05	0,19			0,13				0,03	0,06			0,02			0,03	0,03			0,04
122_Process rule based_med																				
123_Process rule based_high	0,1			0,13	0,78				0,07		0,08	0,02	0,15	0,05		0,17	0,02			0,02
130_Degree of process maturity	0,19	0,16		0,11	0,1	0,03		0,07		0,5	0,21	0,26	0,07			0,11	0,02			0,02
131_Process maturity_low	0,09	0,28			0,02	0,06			0,5				0,04			0,06	0,03			0,04
132_Process maturity_med	0,06			0,11	0,06			0,08	0,21							0,07				
133_Process maturity_high	0,05	0,05		0,06	0,02			0,02	0,26				0,05			0,03				0,04
140_Degree of process complexity	0,1	0,02		0,03	0,19	0,02		0,15	0,07	0,04		0,05		0,11		0,7	0,04			0,04
141_Process complexity_low	0,04			0,03	0,04			0,05					0,11			0,03				
142_Process complexity_med																				
143_Process complexity_high	0,05			0,06	0,14	0,03		0,17	0,11	0,06	0,07	0,03	0,7	0,03			0,04			0,05
150_Degree of process interdependence	0,01				0,04	0,03		0,02	0,02	0,03			0,04			0,04		0,04		1,05
151_Process interdependence_low																	0,04			
152_Process interdependence_med																				
153_Process interdependence_high					0,03	0,04		0,02	0,02	0,04		0,04	0,04			0,05	1,05			
160_Transaction volumes	0,03	0,02			0,01	0,03			0,02	0,03			0,02	0,03						
161_Transaction volume_low	0,02	0,07			0,02	0,11			0,04	0,08										
162_Transaction volume_med																				
163_Transaction volume_high																				
170_Degree of DQ of inputs													0,02				0,09			0,11
171_DQ of input_low																				
172_DQ of input_med																				
173_DQ of input_high																	0,11			0,14
201_Suitable for RPA_positive	0,17	0,01	0,01	0,17	0,25			0,28	0,08		0,04	0,06	0,19	0,04		0,2	0,2	0,01		0,16
211_Suitable for RPA_no sign dif	0,04			0,06					0,06	0,06	0,09	0,06	0,02			0,03				0,04
221_Suitable for RPA_negative	0,14	0,35		0,02	0,12	0,3		0,02	0,23	0,36		0,03	0,05			0,04	0,1			0,11
301_DQ relevance_positive	0,12			0,14	0,18			0,21	0,04			0,05	0,19	0,04		0,18	0,19			0,15
302_DQ relevance_no sign dif																				
303_DQ relevance_negative	0,09	0,29			0,05	0,13		0,02	0,13	0,24			0,02			0,03				
311_DQ reliability_positive	0,12			0,14	0,19			0,22	0,04			0,05	0,21	0,04		0,21	0,18			0,14
312_DQ reliability_no sign dif																				
313_DQ reliability_negative	0,07	0,25			0,03	0,15			0,14	0,27			0,02			0,03				
400 Other benefits	0,01	0,03							0,02			0,03								

Code co-occurrence overall	Process characteristics								Ability to robotize			Data quality						
												A Relevance			B Reliability			
	160_Transaction volumes	161_Transaction volume_low	162_Transaction volume_med	163_Transaction volume_high	170_Degree of DQ of inputs	171_DQ of input_low	172_DQ of input_med	173_DQ of input_high	201_Suitable for RPA_positive	211_Suitable for RPA_no sign dif	221_Suitable for RPA_negative	301_DQ relevance_positive	302_DQ relevance_no sign dif	303_DQ relevance_negative	311_DQ reliability_positive	312_DQ reliability_no sign dif	313_DQ reliability_negative	400 Other benefits
110_Degree of process standardisation	0,03	0,02							0,17	0,04	0,14	0,12		0,09	0,12		0,07	0,01
111_Process standardisation_low	0,02	0,07							0,01		0,35			0,29			0,25	0,03
112_Process standardisation_med									0,01									
113_Process standardisation_high									0,17	0,06	0,02	0,14			0,14			
120_Degree of process rule based	0,01	0,02							0,25		0,12	0,18		0,05	0,19		0,03	
121_Process rule based_low	0,03	0,11									0,3			0,13			0,15	
122_Process rule based_med																		
123_Process rule based_high									0,28		0,02	0,21		0,02	0,22			
130_Degree of process maturity	0,02	0,04							0,08	0,06	0,23	0,04		0,13	0,04		0,14	0,02
131_Process maturity_low	0,03	0,08								0,06	0,36			0,24			0,27	
132_Process maturity_med									0,04	0,09								
133_Process maturity_high									0,06	0,06	0,03	0,05			0,05			0,03
140_Degree of process complexity	0,02				0,02				0,19	0,02	0,05	0,19		0,02	0,21		0,02	
141_Process complexity_low	0,03								0,04			0,04			0,04			
142_Process complexity_med																		
143_Process complexity_high									0,2	0,03	0,04	0,18		0,03	0,21		0,03	
150_Degree of process interdependence					0,09			0,11	0,2		0,1	0,19			0,18			
151_Process interdependence_low									0,01									
152_Process interdependence_med																		
153_Process interdependence_high					0,11			0,14	0,16	0,04	0,11	0,15			0,14			
160_Transaction volumes		0,1		0,73					0,14	0,06	0,02	0,15		0,03	0,13			0,29
161_Transaction volume_low	0,1								0,01		0,04	0,02			0,02			0,07
162_Transaction volume_med																		
163_Transaction volume_high	0,73								0,12	0,07		0,15			0,13			0,25
170_Degree of DQ of inputs						0,31		0,54	0,07		0,09	0,08		0,1	0,08		0,17	0,03
171_DQ of input_low					0,31						0,13			0,17			0,33	
172_DQ of input_med																		
173_DQ of input_high					0,54				0,07			0,09			0,09			
201_Suitable for RPA_positive	0,14	0,01		0,12	0,07			0,07			0,01	0,43			0,44			0,06
211_Suitable for RPA_no sign dif	0,06			0,07														
221_Suitable for RPA_negative	0,02	0,04			0,09	0,13			0,01					0,32			0,35	
301_DQ relevance_positive	0,15	0,02		0,15	0,08			0,09	0,43						0,93			0,07
302_DQ relevance_no sign dif																		
303_DQ relevance_negative	0,03				0,1	0,17					0,32						0,64	
311_DQ reliability_positive	0,13	0,02		0,13	0,08			0,09	0,44			0,93						0,06
312_DQ reliability_no sign dif																		
313_DQ reliability_negative					0,17	0,33					0,35			0,64				
400 Other benefits	0,29	0,07		0,25	0,03				0,06			0,07			0,06			

Appendix E: Metadata of interviews and interviewees

Nr	Code	Function	Recorded time (excl. intro)	Pages in the transcript	Number of codes	Experience
1.	C1	Consultant (Manager) Technology (RPA) - Netherlands	53:32	9	131	>4 years of experience advising various clients from various industries with regard to digital trends, with a major focus on how a digital workforce should be a sustainable part of the existing solution landscape. Certified partner of UiPath.
2.	C2	Consultant (Senior Manager) Finance (RPA) - Netherlands	50:20	17	101	>5 years of experience advising various clients from various industries with regard to digital transformation/digital finance capabilities, with a major focus on the capabilities of robots. Certified partner of UiPath.
3.	B3	RPA consultant & builder - Netherlands	1:14 (recording interrupted)	2 (mostly key outcomes)	78	>2 years of experience with RPA-enabled transformation, both front-office and back-office. Founder of RPA implementation partner for various large (incl. registered) companies and consulting firms. Certified partner of UiPath.
4.	B4	RPA builder - Netherlands	29:14	7	46	>2 years of experience building robots as part of RPA-enabled transformation, and preceded by significant experience with the automation of core business processes. Certified partner of UiPath.
5.	B5	RPA consultant & builder - Netherlands	29:22	9	42	>2 years of experience with RPA-enabled transformation, both front-office and back-office. Founder of RPA implementation partner for various large (incl. registered) companies and consulting firms. Certified partner of UiPath.
6.	B6	RPA consultant & builder - Netherlands	43:58	15	32	>2 years of experience with RPA-enabled transformation, both front-office and back-office. Founder of RPA implementation partner for various large (incl. registered) companies and consulting firms. Certified partner of UiPath.
7.	C7	Consultant (Senior Manager) Technology (RPA) - Switzerland	55:50	11	82	>8 years of experience advising various clients (primarily from the financial services industry) on the automation of business processes, with a major focus (>4 years) on using RPA capabilities to automate smaller-scale business processes.
8.	C8	Consultant (Director) Technology (RPA) Switzerland & Singapore	43:58	9	47	>10 years of experience advising various clients, industries and geographies on how to use technology to optimise business processes, with a major focus (>4 years) on using RPA capabilities.
9.	C9	Consultant (Partner) Technology (RPA) - Netherlands	- (not recorded)	2 (key outcomes)	22	>25 years of experience with various clients and industries in different roles with regard to change management, managing financial processes and process automation, with a major focus (>3 years) on using RPA capabilities and how to utilise RPA in a way that fits the organisational context. Certified partner of UiPath and lecturer at Nyenrode University.
10.	U10	Process improvement manager Financial Shared Services Centre in airline industry - Bulgaria	59:59	9	57	+/- 2 years of hands-on experience with using, building and maintaining robots to automate existing financial (AP/AR/R2R) processes in a shared services centre of a major airline. Acts as an SME for the airline in general, sharing best practices and providing support for other locations that have the intention to utilise robots to automate business or financial processes.
11.	U11	Product Owner RPA / digital consultant	56:22	7	51	+/- 2 years of hands-on experience with defining the corporate strategy of a major airline concerning digital trends, with a major focus on how robotics and artificial intelligence in

		airline industry - Netherlands				general could and should impact the organisation’s orientation towards the future, and how to lay a foundation for pursuing and utilising digital trends in a sustainable, responsible and safe way.