Artificial Intelligence Ethics Taxonomy- Robotic Process Automation (RPA) as business case

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"Clearly, sustained low inflation implies less uncertainty about the future, and lower risk premiums imply higher prices of stocks and other earning assets. We can see that in the inverse relationship exhibited by price/earnings ratios and the rate of inflation in the past. But how do we know when irrational exuberance has unduly escalated asset values, which then become subject to unexpected and prolonged contractions as they have in Japan over the past decade?" (Alan Greenspan, 1996)

ABSTRACT: A Robotic Process Automation (RPA) enabled by Artificial intelligence (AI) has become an important field within the digitalisation of the economy. AI-driven robots and machines are forecasted to grow dramatically in the next years. AI-enabled RPA replaces the work a human would normally do by mimicking interactions with applications and provides direct access to systems using APIs. RPA has superior advantages versus human execution:24x7 execution, eternal lifetime and scalability. Process automatization is per se not a brand-new technology, however due to notable progress in AI, which RPA leverages, it has become an own solution category. RPA enables algorithmic rules without being biased. Ethical considerations intend to make AI-driven RPA more human and introduce morality into the machine learning. The Uber-Waymo trial made transparent how much AI development is influenced by human irrationality and irrational exuberances. It reveals a culture of agile software development, which prioritize releasing the latest software over testing and verification, and one that encourages shortcuts and irrationality. This also give proof that applying AI cannot ensure that irrational exuberances disappear. The reason for this irrational exuberance may have its roots in the exponential growth in computing and storage technologies predicted by Gordon Moore five decades ago. This paper develops a concept how irrational exuberances with the business case of RPA can be prevented from happening. One general approach for solutioning of the issue is to increase transparency. The paper recommends applying technology to make data more accessible and more readable on the application of artificial intelligence. With the aim of application of "transparency technology XBRL (eXtensible Business Reporting Language)" is incorporated. XBRL is part of the choice architecture on regulation by governments (Sunstein, 2013). XBRL is connected to a taxonomy. The paper develops a taxonomy for RPA to make application of artificial intelligence more transparent to the public and incorporates ethical considerations. As a business case the strongly growing RPA industry is selected. The paper focus on the way to enhance AI that aligns with human values. How can incentive be provided that AI systems themselves do not become potential objects of moral concern. The main outcome of the paper is that AI-enabled RPA reveal moral concerns however transparency technologies at the same time also offer way to mitigate such risks

KEYWORDS: Robotic Process Automation (RPA), Irrational exuberances, Artificial Intelligence Ethics, Behavioural Economics, Human-Computer Interaction, Taxonomy, XBRL and Transparency

Introduction

In 2002 "robot-ethics" inaugurated on the IEEE-Robotics and Automation Conference (Malle, 2016). The number of literature on robot-ethics doubled between 2002 and 2014 and the most two discussed questions were how humans should design and deploy robots and secondly what moral capacities robots should consist of? (Tzafestas, 2018).

Robotic Process Automation (RPA) is defined as " tools [which] perform statements on structured data, typically using a combination of user interface interactions, or by connecting to APIs to drive client servers, mainframes or HTML code."(Tornbohm, 2017, van der Aalst et al., 2018, Wisskirchen et al., 2017, Asatiani and Penttinen, 2016). The aim of RPA is to improve the working conditions by replacing simple, repetitive and non- sophisticated tasks by machines (Aguirre and Rodriguez, 2017). An RPA tool operates by mapping a process in the RPA tool language for the software robot to follow, with runtime allocated to execute the script by a control dashboard. A Robotic Process Automation (RPA) enabled by Artificial intelligence (AI) has become an important field within the digitalisation of the economy. An explosion of marketing buzzwords in the RPA space can be observed: "Smart process automation", "cognitive RPA" and "intelligent automation" they all refer in general to the same usage of analytics and artificial intelligence techniques to improve the performance of RPA-driven solutions.

AI-driven robots and machines are forecasted to grow dramatically in the next years and are expected to help to upheave stagnating human productivity (Körner, 2018, Eric Heymann, 2017, Kerremans, 2018). AI-enabled RPA replaces the work a human would normally do by mimicking interactions with applications and also provide direct access to systems using APIs. RPA has superior advantages versus human execution: 24/7 productivity capacities, very low operational costs, eternal lifetime and scalability. Process automatization is per se not a brand-new technology, however due to notable progress in artificial intelligence, which RPA leverages, it has become an own solution category (Chandler et al., 2017).

RPA enables algorithmic rules without being biased. Ethical considerations intend to make AI-driven RPA more human and introduce morality into the machine learning (Bekey, 2012). As robots acquire increasing moral competence, especially moral judgment and decision-making behavioural economics as a theoretical underpinning moves into light. Contemporary hypotheses and investigations have turned behavioural in robotics research (Welch and Roebbers, 2009, Gray et al., 1996, Levy, 2009, Salvini et al., 2010). Behavioral Economics revolutionized standard neo-traditional financial aspects in the previous two decades. From that point forward two Nobel Prizes in Behavioral Economics were crowned as a wide scope of mental, monetary and sociological research center and field tests demonstrated individuals going astray from balanced decisions and standard neo-traditional benefit amplification maxims regularly neglected to clarify how human really act. Individuals rather use heuristics in their everyday basic leadership. These psychological easy routes empower to adapt to a mind-boggling world yet additionally frequently leave people one-sided and falling off track to basic leadership disappointments.

Behavioral Economics identify anomalies and shortfalls in neo-classical economics. Ample evidence showed that human beings disregard rational choices standard neo-classical profit maximization axioms would predict but rather use heuristics in their everyday decision making (Puaschunder 2018b). Due to mental deficiencies, humans are not capable to cope with a complex in transparent world. Contrary to standard neo-classical assumptions, individuals try to mitigate complexity. Reducing complexity also implies decreasing cognitive drain (Beerbaum and Puaschunder, 2019). For many day-to-day problems, humans developed therefore irrational heuristics, which represent mental shortcuts or rule of thumbs, which are frequently applied (Gigerenzer, 1999)

This paper applies behavioural theory to robotic process automation. What are ethical considerations of AI-enabled RPA? What role do ethics play for RPA? In the future age of AI, should we create algorithms that resemble human decision making or strive for rational artificiality? What are the boundaries? How can the external investor receive standardised information with regard to the application of RPA? This paper provides first preliminary answers to this question in having outlined the case of novel RPA. This paper starts to define RPA, continues with the elaboration of the market for RPA. In the next section artificial intelligence ethics is further explained. In the last section the taxonomy for RPA is defined.

Robotic Process Automation (RPA)

At its basic level, RPA is a low impact, scalable and quick-to-implement approach to improving the efficiency of business processes through digital automation. More generally in our world of rapid digitization of operations, many enterprises see RPA as a part of their automation strategy. Benefits of RPA include (Tornbohm, 2017):

Boosting efficiency and productivity with minimal process change:

- RPA offers an alternative to the typical approaches to bring about business change, including building or buying a new system, optimising systems using a BPMS (Business Process Management Software), or outsourcing or shared services. Rather than requiring fundamental process redesign and associated expensive IT-driven transformation, RPA software is able to perform existing business processes by mimicking the way users interact with applications. However, this has an impact on these underlying applications by increasing the load they need to support. In addition, most successful RPA projects involve some degree of process change and optimisation.

Relative Ease of Building Robots:

- RPA tools generally offer a desktop process modelling tool which enables even business users to build complex desktop automation processes in the form of visual workflows. Simple automation processes do not require any code. Figure 1 shows a screenshot of how workflows are used in the desktop environment.

Easily Calculated Savings

- Once a software robot is built, it is easy to understand savings as there is a direct relationship between a robot and an employee's tasks. However, the ability to realise any efficiency gains will depend upon management's willingness to change current business practices.

Processes that are most suited for RPA can be characterised by (van der Aalst et al., 2018):

- High volume of structured digital data
- Relatively fixed processes or user interfaces, which do not change frequently
- Rule-based activities that require little or no cognitive decision making
- Tedious, repetitive and low complexity tasks

RPA tools work best when they have direct access to the data and applications. Thus, processes are more suitable for RPA if they have little or no need for remote access tools.

Processes with unstructured data are not generally suitable for most RPA tools without IA support. If possible, turn data into standardised forms with no unstructured text.

Examples of tasks that RPA software excels at involve large-scale data entry, transfer and validation.

Once IA and cognitive capabilities have matured, a host of new applications will be more suited for automation. Additional examples include:

- Automation of the Preparation of Reports The analysis of a massive dataset or portfolio along with NLG capabilities to create a summary report of findings and suggestions
- Processing of Unstructured Data Dealing with various kinds of unstructured data, including paperwork or scanned documents
- Intelligent Virtual Agents and Chatbots Intelligent agents and chatbots provide the ability to converse with customers to gather information and resolve their recommendation systems, which can be applied to various use cases.

However, it is important to remember that technical support in the form of customisation and integrations are required to suit the platform to a particular use case. It is interesting to note that as a solution becomes increasingly cognitive, more customisation is required. This makes sense because as a solution is built that is smarter for a specific use case, there are inevitably more customisations since processes are not the same, components are generally not out-of-the-box and the cognitive model will have to be trained over a period of time to work well.

Robotic Process Automation (RPA) market

RPA vendors have experienced a significant surge in global interest in the past twelve months (Kerremans, 2018). There has been an evolution in terms of vendor offerings, capabilities, deployment models and market activity. Convergence of RPA and IA Vendors The goal of software robots is to emulate human action using a combination of declarative rules and cognitive techniques and the rules-based techniques have matured. However, when it comes to cognitive capabilities such as NLP, pattern recognition and understanding customers, RPA vendors are at a nascent stage. We expect RPA vendors to either develop these capabilities as part of their core product, or to provide integrations to the likes of IBM Watson, Wipro HOLMES, Microsoft

Cortana and HP Autonomy. In the context of the vendor landscape diagram in Figure 4, RPA vendors are moving to the right, toward incorporating AI capabilities (Tornbohm, 2017, Le Clair et al., 2017).

Virtual Desktop support means that RPA vendors will get increasingly better at automating processes on Virtual Desktops and Citrix environments. Convergence of BPM and RPA Vendors Recognising that software robots could be a critical part of business processes, Pega Systems acquired RPA vendor OpenSpan in April 2016 and have already integrated the products together. We can expect this to continue.

RPA vendors are so varied in terms of offerings, R&D recommends a rigorous capability-based assessment to identify the offering which is best suited to specific use cases:

- Optical Character Recognition (OCR) enables the text in an image to be extracted. These capabilities are useful in virtual desktops & Citrix, where the screen appears as an image.
- Intelligent Document Recognition (IDR) is an extension to OCR that allows the image text to be converted into structured data.
- Natural Language Processing (NLP) is useful as current RPA tools do not interpret the content of the textual data that arises in the workflow. However, some provide the ability to be integrated with an NLP offering. This enables robots to use cognitive capabilities such as understanding context and using judgement where required. This can be shown in a simple use case in the form of a customer support desk ticket resolution system. An NLP engine would enable the robot to understand a submitted message and intelligently categorise it. IDR is a sub-type of NLP.
- Automatic identification of candidate business processes for RPA identify candidate business processes which are suitable for RPA. Users can run a client in the background which gathers data on user activity, and machine learning techniques are used to suggest automation opportunities to the user.
- Natural Language Generation (NLG) involves the collation of data from a number of sources and then the production of a natural language report from this data. For example, Wealth Management firms review and analyse portfolio data, determine meaningful metrics and generate natural language reports for their customers on the investment performance of each of their funds. Generating natural language

reports is a capability of NLG tools such as Narrative Science and Arria. This reduces the time and human effort associated with creating data driven reports.

- Machine Learning techniques enable RPA software to learn from previous activities and to become increasingly efficient and accurate.
- Knowledge Bases and Advanced Exception Management can enhance RPA agents with smart knowledge bases that find new and less-used patterns, memorize those patterns and support agents in the handling of complex exceptions. This allows RPA agents to work out the correct way to deal with situations that might not match pre-compiled rules.

In general, RPA support for Intelligent Automation will take one of two forms:

1. RPA vendors will develop their own AI algorithms and incorporate them into their products
2. RPA vendors will link to AI platforms such as IBM Watson via APIs

Insert Graph 1

Figure 1 outlines the evolution of vendors in the automation and cognitive computing space. In this section, we'll briefly outline each product group (in the RPA and IA space) and identify important related observations.

The market leading products in RPA are Blue Prism, Automation Anywhere and UI Path. All support both attended and unattended modes of execution.

Automation Anywhere and UI Path focus on recording screen activities to form the basis of the process automation, whilst Blue Prism uses a graphical process definition tool. The advantages of the first approach are that it enables business users to define process automations in a very quick and simple manner. The disadvantage is that it is more difficult to maintain these processes if the underlying applications change.

There are many professional service firms and vendors that can help to deliver RPA programmes. These include Accenture, Deloitte, E&Y, TCS, HCL and InfoSys. While these companies can help, thought should be given to the cost of implementation, ownership of IP, maintenance costs and path to production.

WorkFusion covers both supplementary AI support with OCR and IDR and embedded AI, such as experience-based decision-making. AI Platforms such as IBM Watson and Microsoft Cortana provide several artificial intelligence and machine learning techniques including NLP, NLG and Software robots interact with business and desktop applications using a range of techniques.

Robots identify UI elements using a variety of mechanisms. For websites, a simple approach that robots take is to identify fields and buttons by their HTML elements. For .Net applications, robots can inspect the UI code to determine the UI elements. Identifying elements using underlying code makes robots significantly less sensitive to cosmetic changes such as a resized window or a button moved to a new location.

For cases where this is not possible, RPA software must rely on more brittle approaches. Examples include:

- Pixel Location

The simplest method of identifying a field is to point robots to the exact pixel location on the screen where the field exists. As expected, this approach is very fragile as even a simple resize of the window would break the automation.

- Image Recognition

The software robot searches the screen to identify the button. For example, a user indicates what a “Confirm” button looks like and the robot captures an image of the button and looks for it across all pixels on the screen. However, there are issues with this approach. If an element is not currently on the screen, then a basic image recognition approach will not discover it.

Vendors are innovating new methods of performing RPA. For example, some use advanced pattern matching and character recognition approaches to locate visual elements even when their appearance differs slightly from the captured image. These advancements allow the robot to cope with differences in screen resolutions and font styles. This is in fact an example of IA as machine’s intelligence is used.

Intelligent automation refers to the use of analytics and artificial intelligence techniques to further enhance the performance of RPA-driven solutions.

There has been an explosion of marketing buzzwords in the RPA space. “Smart process automation”, “cognitive RPA” and “intelligent automation” all generally refer to the same thing, which includes anything that enhances basic RPA.

It is important to distinguish between AI technology that supplements conventional RPA tools and that which modifies such tools. An example of the former is software that extracts information from unstructured emails for use in RPA. An example of the latter is an RPA process that determines the next action to be performed by using cognitive, experience-based heuristics. In this section, we'll delve into specific examples of intelligent automation:

- Optical Character Recognition (OCR)
- Intelligent Document Recognition (IDR)
- Natural Language Processing (NLP)
- Automatic identification of candidate business processes for RPA
- Natural Language Generation (NLG)
- Machine Learning
- Knowledge Management and Advanced Exception Management

Next, we'll detail the three elements of an RPA tool as seen in Figure 2.

It is important to bear in mind the following concepts:
1) A job is the task that is being automated
2) A robot is a software application that executes jobs
3) A server is an application that schedules and monitors the execution of robots

Insert Graph 2

Robot Developer Tools or Suite:

The developer suite is an environment used to define jobs, which can be defined as the logic a robot follows to perform a business process. As previously explained, developer tools often consist of a process or workflow modeller. Other features can include process recorders, such as Excel's Record Macro feature, and connectors to a range of industry specific applications and databases.

Controller

The Controller controls, monitors and assigns defined jobs. It is often referred to as the Administration or Control Room. Typical features include security and scheduling capabilities.

Software Robots

These are the applications that execute the jobs defined by the robot developer tools and interact with business applications. There are two kinds of RPA software robots:

1) Server based robots that work unattended. They run independently on a server and are triggered by some other event – say, the arrival of an email or a schedule.

2) Desktop based robots that work on attended use cases and are deployed to the worker’s desktop. They are triggered manually by an individual and it runs on their desktop. This area is often referred to as Robotic Desktop Automation. They support a human worker by integrating the data and applications they use in their work to improve efficiency and reduce risk. If there is a process that involves keying in the same information into a number of different applications. RDA could help by allowing a human to key the data in once and then automatically entering the data into multiple applications. RDA does not replace the individual and does not automate the whole process.

Artificial intelligence ethics

AI reflects a large number of algorithms, models and techniques, machine learning, databases and visualizations (Beerbaum and Puaschunder, 2019). AI can be defined as the science and engineering of producing intelligent machines, particularly computer programs, which incorporate intelligence and implies also the task of using computers to understand human intelligence(Moudud-Ul-Huq, 2014). Historically, the process leading to the enormous spread of information and technology is frequently considered as the digital revolution (Körner, 2018). The term implies a revolutionary development from the industrial age to the information age. This transition towards economies and business models reflects the usage of information and communication technology and virtual processes instead of analogue mechanics and face-to-face services. The second half of the last century was dominated by the development of computer technology. This is often referred to as the Third Industrial Revolution, which was driven by the invention of microprocessors that enabled the mass production of personal computers and a very fast increase in storage and computing capacity. Together with the spread of the internet, mobile technology and a strong decrease in costs, it triggered a surge in communication capacities and speed, leading from the industrial into the information or digital age (Körner, 2018). Exponential growth in data availability made the rapid progress in machine learning capabilities possible, considering deep learning and reinforcement learning. This enabled the development of AI systems for pattern selection in big data and a broad range of applications, such as speech/natural language processing, computer vision/image recognition, recommender systems (e.g. in search engines and social networks) and predictive analytics. This founded the basis for virtual personal assistants such as Alexa, Siri or Cortana, which have become first AI-enabled tools used by the mass consumers. Remarkable is the speed with which these radical changes are occurring, and their extensive and comprehensive systemic proliferation have become known as the Fourth Industrial Revolution, as popularized by World Economic Forum founder Klaus Schwab (Beerbaum and Puaschunder, 2019).

The more machine learning systems apply AI becomes powerful it will become more important that ethical frameworks are incorporated machine learning are computational algorithms that use certain characteristics to learn from data using a model (Etzioni and Etzioni, 2017). Robots and algorithms now taking over human decision-making tasks and entering the workforce but also encroaching our private lives, currently challenges legal systems around the globe. The attribution of human legal codes to AI is one of the most ground-breaking contemporary legal and judicial innovations. Until now legal personhood has only been attached directly or indirectly to human entities (Dowell and Tech., 2018). The detachment of legal personhood from human being now remains somewhat of a paradox causing an extent of "fuzziness" of the concept of personhood (Barrat 2013; Solum 1992, p. 1285). As AI gets bestowed with quasi-human rights, defining factors of human personhood will need to be adjusted (Dowell and Tech. 2018). Human concepts, such as morality, ownership, profitability and viability will have different meaning for AI. The need for redefining AIE has therefore reached unprecedented momentum. As predicted trend, the co-existence of AI with the human species is believed to change the fundamental concepts of social, political and legal systems. AI has already produced legal creations and will do so even more in the near future, through its developing autonomy. In addition, the technology leading to AGI and ASI is already present, posing moral and legal dilemmas about who should control it and under what terms. The emergence of AGI and ASI will necessitate the attribution of some extent and of some type of legal personhood, bearing rights and obligations. AI will not be most probably an exact replication of human intellect behavior "[U]ultimately, robots' autonomy raises the question of their nature in the light of the existing legal categories – of whether they should be regarded as natural persons, legal persons, animals or objects – or whether a new category should be created, with its own specific features and implications as regards the attribution of rights and duties" (Committee on Legal Affairs 2016, p. 5). Behavioral economists add the question whether AI and robots should be created to resemble human beings' decision making with fast thinking and fallible choices or rather be targeted at perfect rationality and slow thinking (Kahneman, 2011).

General conscious is strived for so that AI possesses consciousness, which it can evolve and enhance on the basis of its own critical reflection and assessment of external factors. Lower level of autonomy exists if an entity can demonstrate such consciousness at a narrow field or can self-evolve and self-adapt to external influences, thus reaching decisions "of its own," without being conscious of its intelligence as such (Tzimas, 2018).

The Uber-Waymo trial made transparent how much artificial intelligence development is influenced by human irrationality and irrational exuberances. It reveals a culture of agile software development, which prioritize releasing the latest software over testing and verification, and one that encourages shortcuts and irrationality. This also give proof that applying artificial intelligence cannot ensure that irrational exuberances are prevented. The reason for this irrational exuberance may have its roots in the exponential growth in computing and storage technologies predicted by Gordon Moore five decades ago. This paper develops a concept how irrational exuberances from RPA can be prevented from happening. One general approach for solutioning of the issue is to increase transparency. The paper recommends applying technology to make data more accessible and more readable on the application of artificial intelligence. For this purpose, the application of "transparency technology XBRL (eXtensible Business Reporting Language)" is incorporated. XBRL is part of the choice architecture on regulation by governments (Sunstein, 2013), which applies nudging for influencing towards a preferred option used by the mass consumers. XBRL is connected to a taxonomy. The paper develops a taxonomy to make application of artificial intelligence more transparent to the public and incorporates ethical considerations. As a business case the strongly growing RPA market is selected. The paper focus on the way to enhance AI that aligns with human values. How can incentive be provided that AI systems themselves do not become potential objects of moral concern. The main outcome of the paper is that Digitalization implies with AI moral concerns however transparency technologies at the same time also offer way to mitigate such risks.

The pace of technological development has gained such speed that corporates, consumers and governments often find themselves struggling to keep pace. Developments in AI have far-reaching economic and socio-political consequences, some of them are already materializing. However, it is still unclear, what will be the exact impact on human society. How will AI and robotics lead to the allocation of labour and capital, so will whole society improve? When people decide, limitations in their capacity to foresee long-term impacts and the collective outcomes of their choices can contribute to institutional downfalls. Emergent risks can have crucial impacts in the finance domain as the 2008/09 World Financial Crisis outlined

Robotic Process Automation (RPA) Taxonomy

This paper develops a taxonomy for RPA to make application of artificial intelligence more transparent to the public and incorporates ethical considerations. For this purpose, the "transparency technology XBRL (eXtensible Business Reporting Language)" is incorporated. XBRL is part of the choice architecture on regulation by governments (Sunstein, 2013). XBRL is connected to a taxonomy. As a business case the strongly growing RPA industry is selected. The paper focus on the way to enhance AI that aligns with human values. How can incentive be provided that AI-enabled RPA themselves do not become potential objects of moral concern.

The taxonomy development in the context of XBRL considering the academic literature reflects the following objectives:

- Enable the investors to get corporate information, which are technically readable and enable to compare company behaviour among its peers non-peers by following standardized reporting disclosures (Arnold et al., 2012)
- Enable to become compliant with regulations, in terms of disclosing information in accordance with local and international rules (Piechocki, 2009)
- Improve the financial and non-financial communication by enabling adoption of specific branch requirements of industry (banks, insurance etc.) and of business variations

However, XBRL is bounded to a taxonomy (Piechocki et al., 2007) as functionality is only guaranteed with the existence of a taxonomy. Given the complexity of principles-based taxonomies, AI can achieve a better representation between the taxonomy and underlying regulations (Mwilu, Prat and Comyn-Wattiau 2015) due to enhanced learning curves and computational power.

Machine learning systems for principles-based accounting taxonomies need to consider the following:

- Programming AI should not only reflect their own ethical view, however designed to act accordingly the aggregate ethical views of society
- Codes for designing taxonomies used by machine learning systems need to be made transparent to the public, as otherwise a nudgital divide in the digital age may occur within society

- AI needs to reflect human decision making, as information is used for decision usefulness
- Information on potential emergent risks that emerge in complex interactive systems by collective outcomes of individual decision-making fallibility over time is required

RPA- AI-Ethics Taxonomy — Transition risk:

- Risk of Operational Failure
  - Safety: AI-enabled RPA should be safe and secure throughout the operational lifetime and verifiably so where applicable and feasible
  - Failure of transparency: If an AI system causes harm, it should be possible to ascertain why and provide such transparency to the client
  - Judicial Transparency: Any involvement by an autonomous system in judicial decision-making should provide a satisfactory explanation auditable by a competent human authority
  - Human Control: Humans should choose how and whether to delegate decisions to AI systems, to accomplish human-chosen objectives and to ensure that human profiles are correctly interpreted by the machines

- Risk of Value Misalignment
  - Principal-agent conflict: Designers and builders of advanced AI-enabled RPA systems are stakeholders in the moral implications of their use, misuse, and actions, with a responsibility and opportunity to shape those implications
  - Human Values: AI systems should be designed and operated to be compatible with ideals of human dignity, rights, freedoms, and cultural diversity
  - Non-subversion: The power conferred by control of highly advanced AI systems should respect and improve, rather than subvert, the social and civic processes on which the health of society depends
  - Common Good: Superintelligence should only be developed in the service of widely shared ethical ideals, and for the benefit of all humanity rather than one state or organization
- Risk of failure due to autonomous decision making

  - Value Alignment: Highly autonomous AI systems should be designed so that their goals and behaviours can be assured to align with human values throughout their operation
  - Human control: Human interaction is required to control internally functionality of autonomous systems
  - AI-Arms Race: An arms race in lethal autonomous weapons should be avoided.
  - Recursive Self-improvement: AI systems designed to recursively self-improve or self-replicate in a manner that could lead to rapidly increasing quality or quantity must be subject to strict safety and control measures

- Risk of negligence
  - Capability Caution: There being no consensus, we should avoid strong assumptions regarding upper limits on future AI capabilities.
  - Importance: Advanced AI could represent a profound change in the history of life on Earth, and should be planned for and managed with commensurate care and resources
  - Shared benefit: AI technologies should benefit and empower as many people as possible

RPA-AI-Ethics Taxonomy — Physical Risk

The following reporting elements define the second channel on physical risk

  - Supply Chain Risk
    - Sales impact due supply chain risk impacted by AI-failure risk leading to distribution delays, supply shortage and high price sensitivity
    - Resource demand of dependency of natural resources leading to supply shortage and high input cost
  - Operational Risk
    - Risks posed by AI systems, especially catastrophic or existential risks, must be subject to planning and mitigation efforts commensurate with their expected impact.
    - Socio-economic: Access to AI leading to migration and economic disruption leading to business interruptions, political instability and social license to operate

  - Market Risk

- Sales impacted by ethical risk leading to interruptions at point of sale, migration conflict and risk of political disruption
- Autonomous systems might become uncontrollable and
- Control measures might not be effective or also done by machines due to efficiency and leading to further risk of failure

Conclusions

This paper conceptualizes ethical questions arising from robotic process automation within the Human-Computer interaction: how the algorithms should be designed for decision usefulness. Should the objective be to reflect human decision making or rational artificiality? Overall this article plays an important role in the evaluation of nudging and its influence on the stability of economic markets and societal systems.

Globalization led to an intricate set of interactive relationships between individuals, organizations and states. Unprecedented global interaction possibilities have made communication more complex than ever before in history as the whole has different properties than the sum of its increasing diversified parts. Electronic outsourcing in the age of AI is likely to increase and with this trend a possible nudgital divide in the 21st century (Puaschunder 2017b). In the light of growing tendencies of globalization, the demand for an in-depth understanding of how information will be shared around the globe and AI hubs may evolve in economically more developed parts of the world has gained unprecedented momentum. Another predictable trend in the wake of the artificial intelligence revolution will feature time. AI with eternal life and 24/7 productivity capacities will change tact. Inequality will become another area of interest drawing on the future vision that central rational AI-hubs will outperform underdeveloped remote areas of the world even more in the digital age.

The Uber-Waymo trial made transparent how much artificial intelligence development is influenced by human irrationality and irrational exuberances. It reveals a culture of agile software development, which prioritize releasing the latest software over testing and verification, and one that encourages shortcuts and irrationality.

Future research in a truly interdisciplinary fashion could explore the most novel cutting-edge questions on the behavioral analysis frontier (Puaschunder, forthcoming). What is the role of behavioral finance in guiding AI? What role do ethics play for behavioral economists? Do big data driven results impose critical privacy concerns? In the future age of A, should we create algorithms that resemble human decision making or strive for rational artificiality? What are the boundaries of the extension of behavioral insights? And does nudging in the wake of libertarian paternalism entail a social class division into those who nudge and those who are nudged? This paper provides first preliminary answers to this question in having outlined the case of novel AI technologies at the forefront of Behavioralism and Behavioral Economic Analysis in order to provide future thought-provoking simulations. Future research in a truly interdisciplinary fashion could explore the most novel cutting-edge questions on the behavioral analysis frontier. What is it that makes human humane? In the age of AI and automated control, humanness is key to future success. Future research should draw from behavioral human decision-making insights and evolutionary economics in order to outline what makes human humane and how human decision making is unique to set us apart from AI rationality.

The paper recommends applying technology to make data more accessible and more readable on the application of artificial intelligence. For this purpose, the application of "transparency technology XBRL (eXtensible Business Reporting Language)" is incorporated. The paper develops a taxonomy to make application of artificial intelligence more transparent to the public and incorporates ethical considerations. As a business case the strongly growing RPA market. The paper focus on the way to enhance AI that aligns with human values. How can incentive be provided that AI systems themselves do not become potential objects of moral concern. The main outcome of the paper is that Digitalization implies with AI moral concerns however transparency technologies at the same time also offer way to mitigate such risks.

The findings promise to hold novel insights for future success factors for human resource management but also invaluable contributions for AI ethics. Having parts of the world being AI-driven and others being human capital grounded is prospected to increase the international development divide in the years to come. While in the AI-hubs human will be incentivized to become more creative and humane while AI performs all rational tasks to a maximum productivity, other parts of the world will naturally fall back as for being stuck in spending human capital time on machine-outsourceable tasks and not honing humane skills, which are not replicable by machines. It remains on academic fore thinkers and well-informed market specialists to work together in shedding light on potential ethical infringements in the transition to an AI-driven economy.

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Figure 1: RPA Market

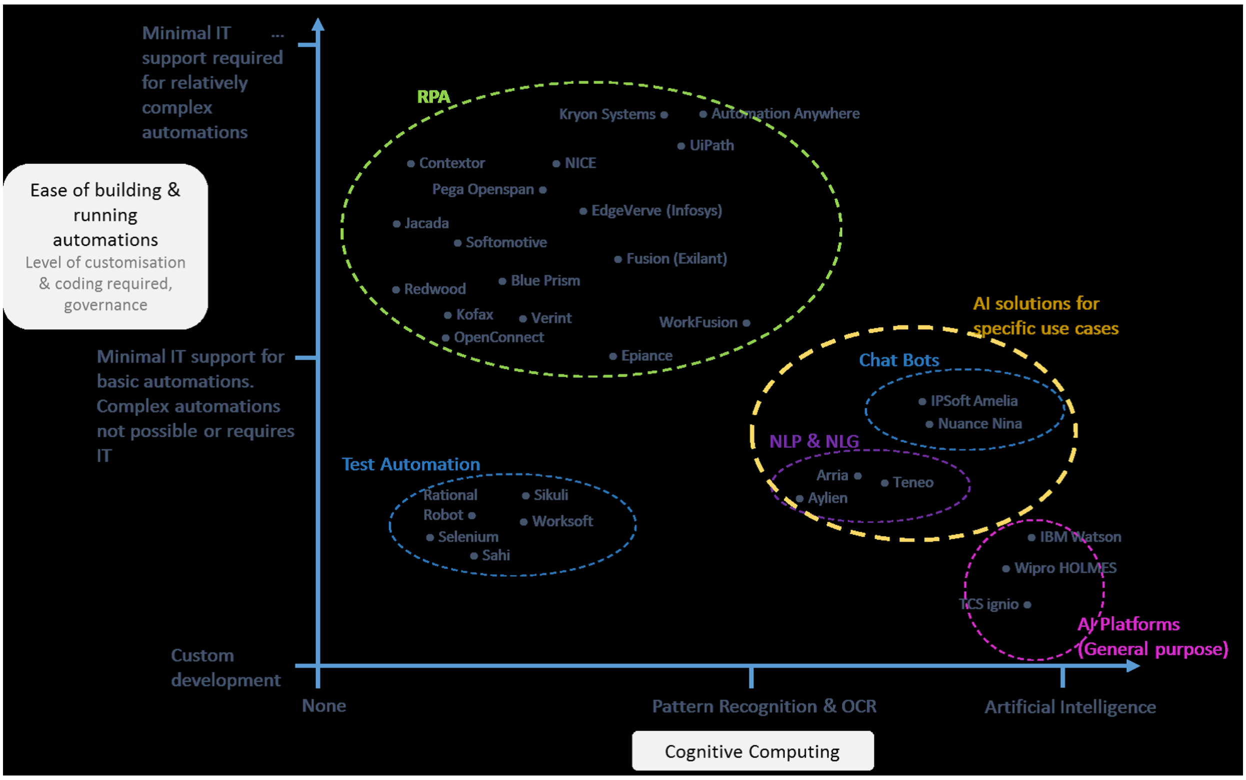

Figure 2: RPA process