ATLANTIS PRESS

Advances in Social Science, Education and Humanities Research, volume 211

10th International RAIS Conference on Social Sciences and Humanities (RAIS 2018)

A Behavioral Economics Approach to Digitalisation – The Case of a Principles-based Taxonomy

Dirk Beerbaum[1] and Julia M. Puaschunder[2]

[1]*Aalto University School of Business, Department of Accounting, Helsinki, Finland, Dirk.Beerbaum@aalto.fi Frankfurt School of Finance & Management, Frankfurt am Main, dbeerbaum@fs.de*

[2]*The New School, Department of Economics, Schwartz Center for Economic Policy Analysis, Columbia University, Graduate School of Arts, New York, Julia.Puaschunder@columbia.edu, Princeton University, Julia.Puaschunder@princeton.edu, George Washington University, jpuaschunder@gwu.edu*

ABSTRACT: A growing body of academic research in the field of behavioural economics, political science and psychology demonstrate how an invisible hand can nudge people's decisions towards a preferred option. Contrary to the assumptions of the neoclassical economics, supporters of nudging argue that people have problems coping with a complex world, because of their limited knowledge and their restricted rationality. Technological improvement in the age of information has increased the possibilities to control the innocent social media users or penalise private investors and reap the benefits of their existence in hidden persuasion and discrimination. Nudging enables nudgers to plunder the simple uneducated and uninformed citizen and investor, who is neither aware of the nudging strategies nor able to oversee the tactics used by the nudgers (Puaschunder 2017a, b; 2018a, b). The nudgers are thereby legally protected by democratically assigned positions they hold. The law of motion of the nudging societies holds an unequal concentration of power of those who have access to compiled data and coding rules, relevant for political power and influencing the investor's decision usefulness (Puaschunder 2017a, b; 2018a, b). This paper takes as a case the "transparency technology XBRL (e*X*tensible *B*usiness *R*eporting *L*anguage)" (Sunstein 2013, 20), which should make data more accessible as well as usable for private investors. It is part of the choice architecture on regulation by governments (Sunstein 2013). However, XBRL is bounded to a taxonomy (Piechocki and Felden 2007). Considering theoretical literature and field research, a representation issue (Beerbaum, Piechocki and Weber 2017) for principles-based accounting taxonomies exists, which intelligent machines applying Artificial Intelligence (AI) (Mwilu, Prat and Comyn-Wattiau 2015) nudge to facilitate decision usefulness. This paper conceptualizes ethical questions arising from the taxonomy engineering based on machine learning systems: Should the objective of the coding rule be to support or to influence human decision making or rational artificiality? This paper therefore advocates for a democratisation of information, education and transparency about nudges and coding rules (Puaschunder 2017a, b; 2018a, b).

KEYWORDS: Artificial Intelligence Ethics, Behavioural Economics, Digitalisation, Human-Computer Interaction, Nudging, Principles-based Taxonomy and XBRL, Taxonomy

Introduction

Contemporary theories and studies of economics have turned behavioral. Behavioral Economics revolutionized mainstream neo-classical economics in the past two decades. Since then two Nobel Prizes in Economics have crowned this growing field as a wide range of psychological, economic and sociological laboratory and field experiments proved human beings deviating from rational choices and standard neo-classical profit maximization axioms often failed to explain how human actually behave (Puaschunder, forthcoming). Human beings rather use heuristics in their day-to-day decision making. These mental short cuts enable to cope with a complex world yet also often leave individuals biased and falling astray to decision making failures (Puaschunder, forthcoming). Research in Political Science about voting decision from people shows that they are strongly influenced by rather unreflective first impressions and those decisions are not the outcome of rational reflection and deliberation (Todorov 2005).

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 unable to cope with a complex world and fall prey to complexity. Contrary to standard neo-classical assumptions, individuals try to reduce

complexity, whenever it is possible (Puaschunder 2018b). Reducing complexity also implies decreasing cognitive drain on our limited mental resources. For many day-to-day problems, humans developed certain heuristics, which represent mental shortcuts or rule of thumbs, which are very successfully applied (Gigerenzer 1999; Puaschunder 2018b).

Behavioral Economics revolutionized decision making theory. Laboratory experiments have captured heuristics as mental short-cuts easing choices of mentally constrained human in a complex world (Puaschunder 2018b). At the same time, heuristics were examined as a source of downfalls on rational and socially-wise choices given future uncertainty (Puaschunder 2018b). Behavioral economists have recently started to nudge – and most recently wink – people into favorable decision outcomes, offering promising avenues to steer social responsibility in public affairs (Puaschunder 2018b).

What followed was the powerful extension of behavioral insights for public policy making, international development and decision usefulness (Puaschunder 2018b, forthcoming). Behavioral economists proposed to nudge and wink citizens to make better choices for them and the community around the globe (Puaschunder 2018b, forthcoming). Many different applications of rational coordination followed ranging from improved organ donations, health, wealth and time management, to name a few (Puaschunder 2018b, forthcoming). Starting with the beginning of the entrance of behavioral aspects in economic analyses and intercultural differences in behavioral understandings, the paper will then embark on a wide range of classic behavioral economics extensions in order to guide a powerful application to AI in the age of the digitalisation of the economy (Puaschunder, work in progress).

This paper applies behavioral economics to an issue appearing in the area of investor decision usefulness caused by the digitalisation of the economy in a truly interdisciplinary way. 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 AI, 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 (Puaschunder, work in progress).

Nudging in the Digital Age

Academic research focusing on nudging is rarely pursued in an online context. While the motivation behind nudging appears as a noble endeavor to foster peoples' lives around the world in very many different ways, the nudging approach raises questions of social hierarchy and class division (Puaschunder 2017a, b; 2018a, b). The motivating force of the nudgital society may open a gate of exploitation of the populace and – based on privacy infringements – stripping them involuntarily from their own decision power in the shadow of legally-permitted libertarian paternalism under the cloak of the noble goal of welfare-improving global governance (Puaschunder 2017a, b; 2018a, b). Nudging enables nudgers to plunder the simple uneducated citizen, who is neither aware of the nudging strategies nor able to oversee the tactics used by the nudgers (Puaschunder 2017a, b; 2018a, b). The nudgers are thereby legally protected by democratically assigned positions they hold or by outsourcing strategies used, in which social media plays a crucial rule (Puaschunder 2017a, b; 2018a, b). Social media forces are captured as unfolding a class dividing nudgital society, in which the provider of social communication tools can reap surplus value from the information shared of social media users (Puaschunder 2017a, b; 2018a, b). The social media provider thereby becomes a capitalist-industrialist, who benefits from the information shared by social media users, or so-called consumer-workers, who share private information in their wish to interact with friends and communicate to public (Puaschunder 2017a, b; 2018a, b). The social media capitalist-industrialist reaps surplus value from the social media consumer-workers' information sharing, which stems from nudging social media users (Puaschunder 2017a, b; 2018a, b). For one, social media space can be sold to marketers who can constantly penetrate the consumer-worker in a subliminal way with

advertisements (Puaschunder 2017a, b; 2018a, b). But also nudging occurs as the big data compiled about the social media consumer-worker can be resold to marketers and technocrats to draw inferences about consumer choices, contemporary market trends or individual personality cues used for governance control, such as, for instance, border protection and tax compliance purposes (Puaschunder 2017a, b; 2018a, b). Economics has recently gained interest in *robo economics*, with socio-economics and sociology driven results on the entrance of financial roboadvisors (Hayes 2018). This important research sheds light on the new class of digital financial advisor, roboadvisors, that provide investment management online with minimal human intervention. As such, this upcoming research stream is at the forefront of giving practical advice on the transition to a human-robot diversified market economy.

Thereby the law of motion of the nudging societies holds an unequal concentration of power of those who have access to compiled data and who abuse their position under the cloak of hidden persuasion and in the shadow of paternalism (Puaschunder 2017a, b; 2018a, b). In the nudgital society, information, education and differing social classes determine who the nudgers and who the nudged are (Puaschunder 2017a, b; 2018a, b). Humans end in different silos or bubbles that differ in who has power and control and who is deceived and being ruled (Puaschunder 2017a, b; 2018a, b). The owners of the means of governance are able to reap a surplus value in a hidden persuasion, protected by the legal vacuum to curb libertarian paternalism, in the moral shadow of the unnoticeable guidance and under the cloak of the presumption that some know what is more rational than others (Puaschunder 2017a, b; 2018a, b). All these features lead to an unprecedented contemporary class struggle between the nudgers (those who nudge) and the nudged (those who are nudged), who are divided by the implicit means of governance in the digital scenery (Puaschunder 2017a, b; 2018a, b). In this light, governing our common welfare through deceptive means and outsourced governance on social media appears critical. In combination with the underlying assumption of the nudgers knowing better what is right, just and fair within society, the digital age and social media tools hold potential unprecedented ethical challenges (Puaschunder 2017a, b; 2018a, b). The implicit hidden persuasion of libertarian paternalism therefore opens a gate to deception and is an unprecedented social class division means (Puaschunder 2017a, b; 2018a, b).

To draw attention to this implicit struggle within society is important for various reasons: Addressing the nudgital society allows to better understand the laws of motion of governance in the digital age, leading to the potentially unequal accumulation and concentration of power (Puaschunder 2017a, b; 2018a, b). Further consequences may be e-outsourcing and concentrations of AI hubs with potential to reap information sharing benefits from around the world (Puaschunder 2017a, b, 2018a, b). Technological improvement in the age of information has increased the possibilities to control the innocent social media users and reap the benefits of their existence in hidden persuasion (Puaschunder 2017a, b; 2018a, b). In the age of populism, nudging can be criticized to be used by the ruling class to exploit the governed populace. In modern democracies, the right to rule was recently proven to be plundered in democratic votes through misguiding information of alternative facts and fake news circulated on social media (Puaschunder 2017a, b; 2018a, b). The socio-ethical crises that are rooted in the contradictory class division of the nudgital society are presented in this paper for the first time and from there on demand for further description and research on capitalism and democracy in the digital age. (Puaschunder 2017a, b; 2018a, b) This paper therefore advocates for a democratisation of information, education about nudges and well-informed distribution of transparent governance control (Puaschunder 2017a, b; 2018a, b). AI will be portrayed to hold advantages of 24/7 productivity hubs that may increase the international development divide throughout the world (Puaschunder, work in progress). While innovative AI hubs may reap benefits from around the globe, human capital driven remainders may fall back even worse as for being stuck in the spending time for tasks already performed by AI in other parts of the world (Puaschunder, work in progress).

Democratisation of digital information: XBRL

As one of the newest trends in Behavioral Economics, governments around the world nowadays apply behavioral economic models (Sunstein 2013) for choice architecture on regulation. Behaviorally

informed tools for external disclosure are selected by governments (Sunstein 2013). To make data more accessible and more readable, regulators impose flexible "transparency technology XBRL (e*X*tensible *B*usiness *R*eporting *L*anguage)" (Sunstein 2013, 20) in the digital age. It is part of the choice architecture on regulation by governments (Sunstein 2013), which applies nudging for influencing towards a preferred option. XBRL was not originally invented by behavioral economists, but by a Certified Public Accountant (CPA) named Charles Hoffman in 1998 and represents an open standard for electronic reporting and the exchange of data (Cohen, Schiavina and Servais 2005; Mirsch, Lehrer and Jung 2017; Sunstein 2013; Weinmann, Schneider and vom Brocke 2016) and should enable a democratisation of the information access. XBRL inevitably requires the usage of an adequate taxonomy (Kurt and David 2003). The taxonomy development in the context of XBRL considering the academic literature reflects the following objectives:

- Enable the investors to receive corporate information, which are technically readable and comparable information based on country-by-country or sector analysis and thus improve transparency (Arnold, Bedard, Phillips and Sutton 2012).
- Enable the preparers to fulfill compliance requirements set by regulators, 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 (Swanson, Durler and Remington 2007).

However, XBRL is bounded to a taxonomy (Piechocki and Felden 2007), as functionality is only guaranteed with the existence of a taxonomy (Debreceny et al. 2009). 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. According to most recent literature (Zhang et al. 2018), behavioral economics approaches are applied to solve the representation issue for financial reporting with principles-based taxonomy. Such issues in accounting cannot be solved with standard-conventional techniques. This implies a democratic accountability, which is also enabled by the recent advances in information technology (McKernan and McPhail 2012).

According to Roe and Thomas (2013), there exists no standard way to build up a taxonomy. Taxonomies can be developed for several reasons (Thietart 2001) and different approaches exist from software, knowledge and ontology development for XBRL engineering (Debreceny et al. 2009). There is a best practice release by XBRL International, the "Financial Reporting Taxonomy Architecture (FRAT)" (Hamscher et al. 2006), which defines modelling rules for XBRL taxonomy development (Debreceny 2009). However, this model focuses on technical aspects of how business rules are implemented in a specific XBRL taxonomy, and aspects of software engineering are integrated within this model. From a holistic point of view, the taxonomy development process encompasses reporting elements, technical XBRL specification and testing.

Existing approaches for the methodology of the development and engineering of a taxonomy in the academic literature share a focus on the technical aspects of the taxonomy development process via engineering models (Piechocki and Felden 2007). The following overview follows the objective to integrate business-rule development with the taxonomy development.

- In the preparatory phase, reporting elements need to be defined and the associated meta-data, including specifications of the taxonomy and its intended use.
- A building phase follows, which focus on technical considerations, application rules on the base taxonomy and the management of extensions.
- Finally, there is a maintenance and evolution phase for the management and development of the taxonomy on a continued basis.

To nudge or not – Principles-based versus rule-based accounting taxonomy

Historically, the academic literature treats the discussion on principles-based vs. rule-based debate since many years (Benston, Bromwich and Wagenhofer 2006). The principles-based vs. rule-based debate in the U.S. was then rediscussed after the Enron and WorldCom accounting scandal 2002

(Nobes 2005). This included an intense discussion whether US GAAP should become more principles-based, as rules-based standards might give rise to "cook-book accounting", without considering a substance-over-form approach (Parfet 2000). So if there is no discretion to the chef, the taste will always be the same. US GAAP tends to be mechanical and inflexible. Clear-cut rules bear advantages as no costs for interpretation optionality are incurred bypreaprers, however it encounters the risk that this approach motivates financial engineering to circumvent the rules as the academic literature about tax avoidance give proof (Healy and Palepu 2003). According to Nelson (2003) a standard should not be seen as only principles or rule-based but should rather be regarded as more or less rule-based. According to a behavioral analysis Nelson concludes that rules can improve the accuracy of the communication of the standard setter and reduce imprecision associated with aggressive reporting due to unawareness of existing rules (Nelson 2003).

Positive accounting intends to develop a theory that is capable of explaining observed phenomena. Normative accounting whereas prescribes the practical implementation of accounting. Principles-based accounting can be structured to normative accounting, while rule-based accounting considers concepts about positive accounting. Normative challenges exist for the principles-based taxonomy, as companies have to incorporate judgments into corporate reporting. Therefore, principles-based accounting taxonomies undergo a continuous conflict with rule-based accounting.

However based on recent literature a representation and structural conflict (Beerbaum, Piechocki and Weber 2017) for principles-based taxonomies exist. Such issues in accounting can not be solved with standard-conventional techniques. Behavioral economics approaches are used to predict equilibrium (Zhang et al. 2018). Given the complexity of principles-based taxonomies, AI – due its learning curves – achieves a better representation between the taxonomy and underlying regulations (Mwilu, Prat, & Comyn-Wattiau 2015). According to most recent literature (Zhang et al. 2018) behavioral economics approaches are applied for financial reporting with principles-based taxonomy, which leads to lower extension rates, i.e., deviations from the base 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. Regulators require a flexible technology to access relevant information. This implies a democratic accountability, which is also enabled by the recent advances in information technology (McKernan and McPhail 2012).

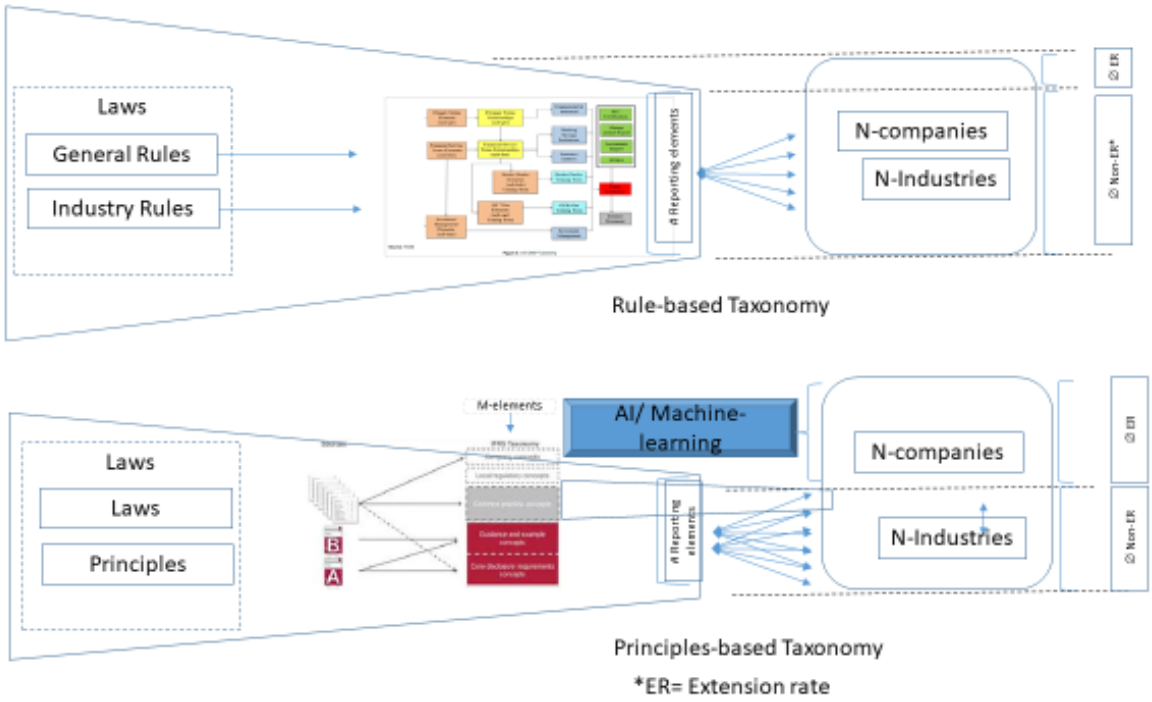

Figure 1. Rule-based versus Principles-based Taxonomy

Artificial intelligence ethics

AI reflects a large number of algorithms, models and techniques, machine learning, databases and visualizations (Moudud-Ul-Huq 2014). According to McCarthy (2007) 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. Historically, the process leading to the enormous spread of information and technology is frequently considered as the digital revolution. 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 (Moudud-Ul-Huq 2014). 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 (Dosi, Galambos and Gambardella 2013). 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. 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 (Hasperué 2015). 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 popularised by World Economic Forum founder Klaus Schwab (Kemp 2016).

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 sociopolitical consequences, some of them are already materializing (Körner 2018). 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? 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 (Centeno et al. 2013).

The more machine learning systems apply AI becomes powerful it will become more important that ethical frameworks are incorporated (Picard 1997; Puaschunder, work in progress). According to Samuel (1959) machine learning are computational algorithms that use certain characteristics to learn from data using a model. 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 (Baum 2017)
- 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 (Moudud-Ul-Huq 2014)
- Information on potential emergent risks that emerge in complex interactive systems by collective outcomes of individual decision making fallibility over time is required

Conclusions

This paper conceptualize ethical questions arising from machine learning systems within the Human-Computer interaction: how should the algorithms 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. Depicting nudging during this unprecedented time of economic change and regulatory reform holds invaluable historic opportunities for global governance policy makers to snapshot nudgital potential in the digital age and bestow market actors with future-oriented skills (Puaschunder 2018a). The results guide a successful nudging implementation to lower systemic economic market downfalls with attention to the changes implied in the wake of the ongoing AI revolution. Market and societal policy recommendations for global governance experts on how to strengthen society by nudges but also overcome unknown emergent risks within globalized markets and bestow market actors with key qualifications in a digitalized world are offered (Puaschunder 2017a, b; 2018a, b).

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 (Puaschunder, work in progress). 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 (Puaschunder, work in progress).

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 (Puaschunder, work in progress).

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 forethinkers and well-informed market specialists to work together in shedding light on potential ethical infringements in the transition to an AI-driven economy.

References

Arnold, V., J. C. Bedard, J. R. Phillips, and S. G. Sutton. 2012. "The impact of tagging qualitative financial information on investor decision making: Implications for XBRL." *International Journal of Accounting Information Systems* 13 (1): 2-20

Baum, S.D. 2017. "Social choice ethics in artificial intelligence." *AI & SOCIETY*:1-12. DOI: 10.1007/s00146-017-0760-1.
Beerbaum, D., M. Piechocki, and C. Weber. 2017. "Is there a conflict between principles-based standard setting and structured electronic reporting with XBRL?" In *European Financial and Accounting Journal* 12(3): 33-52.
Benston, G. J., M. Bromwich, and A. Wagenhofer. 2006. "Principles-versus rules-based accounting standards: the FASB's standard setting strategy." *Abacus* 42 (2): 165-188.
Centeno, M. A., A. N. Creager, A. Elga, E. Felton, S. N. Katz, W. A. Massey, and J. N. Shapiro. 2013. *Global systemic risk: Proposal for a research community*. Unpublished working paper, April 1:2013.
Debreceny, R., C. Felden, B. Ochocki, M. Piechocki, and M. Piechocki. 2009. "XBRL Taxonomy Engineering." In *XBRL for Interactive Data*. New York: Springer, 113-127.
Dosi, G., L. Galambos, and A. Gambardella. 2013. *The third industrial revolution in global business*. Cambridge University Press.
Gigerenzer, G. 1999. *Simple heuristics that make us smart*, edited by P. M. Todd. New York: Oxford University Press.
Hamscher, W., M. Goodhand, C. Hoffman, B. Homer, J. MacDonald, G. Shuetrim, and H. Wallis. 15/5/2015. "Financial reporting taxonomies architecture 1.0." Technical report, *XBRL* 2006 [cited 15/5/2015]. Available from xbrl.org.
Hasperué, W. 2015. "The master algorithm: how the quest for the ultimate learning machine will remake our world." *Journal of Computer Science and Technology* 15 (2): 157-158.
Hayes, A. (2018). *The active construction of passive investors: Toward robo economicus*. Madison, WI: University of Wisconsin-Madison, Department of Sociology.
Healy, P. M., and K. G. Palepu. 2003. "The fall of Enron." *The Journal of Economic Perspectives* 17 (2): 3-26.
Kemp, R. 2016. "Fourth industrial revolution." *The Lawyer* 31 (21): 12.
Körner, K. 2018. "Digital Economics." *Deutsche Bank Research*. EU Monitor.
Maines, L. A., E. Bartov, P. Fairfield, D. E. Hirst, T. E. Iannaconi, R. Mallett, C. M. Schrand, D. J. Skinner, and L. Vincent. 2003. "Evaluating concepts-based vs. rules-based approaches to standard setting." *Accounting Horizons* 17 (1): 73-89.
McCarthy, J. 2007. "From here to human-level AI." *Artificial Intelligence* 171 (18): 1174-1182.
McKernan, J. F., and K. McPhail. 2012. "Accountability and Accounterability." *Critical perspectives on accounting* 23 (3): 177-182.
Moudud-Ul-Huq, S. 2014. "The role of artificial intelligence in the development of accounting systems: A review." *IUP Journal of Accounting Research & Audit Practices* 13 (2): 7-19.
Mwilu, O., N. Prat, and I. Comyn-Wattiau. 2015. "Taxonomy development for complex emerging technologies–The case of Business Intelligence and Analytics On the cloud." Paper read at *PACIS* 2015.
Nelson, M. W. 2003. "Behavioral evidence on the effects of principles-and rules-based standards." *Accounting Horizons* 17 (1):91-104.
Nobes, C. W. 2005. "Rules-based standards and the lack of principles in accounting." *Accounting Horizons* 19 (1): 25-34.
Parfet, W. U. 2000. "Accounting subjectivity and earnings management: A preparer perspective." *Accounting Horizons* 14 (4):481-488.
Picard, R. 1997. *Affective computing*. Cambridge, MA: MIT Press. MA Google Scholar.
Piechocki, M., and C. Felden. 2007. "XBRL Taxonomy Engineering. Definition of XBRL Taxonomy Development Process Model." In *ECIS*, 889-900.
Piechocki, M., Felden, C., Gräning, A., Debreceny, R. . 2009. "Design and standardisation of XBRL solutions for governance and transparency." *International Journal of Disclosure and Governance* 6 (3): 224–240.
Puaschunder, J. M. 2017a. "Nudgital: Critique of Behavioral Political Economy." *Archives of Business Research* 5(9): 54-76.
Puaschunder, J. M. 2017b. "The nudging divide in the digital big data era." *International Journal of Research in Business, Economics and Management* 4 (11-12): 49-53.
Puaschunder, J. M. 2018a. "Nudging in the digital big data era." *European Journal of Economics, Law and Politics* 4 (4): 18-23.
Puaschunder, J. M. 2018b. "Nugitize me! A behavioral finance approach to minimze losses and maximize profits from heuristics and biases." *International Journal of Management Excellence* 10 (2): 1241-1256.
Puaschunder, J. M. (forthcoming). Towards a utility theory of privacy and information sharing and the introduction of hyper-hyperbolic discounting in the digital big data age. Encyclopedia of Information Science and Technology. Hershey, PA: IGI.
Puaschunder, J. M. (work in progress). Artificial Intelligence Ethics. Social Science Research Network working paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3137926.
Roe, S. K., and A. R. Thomas. 2013. The Thesaurus: Review, Renaissance, and Revision: Taylor & Francis.
Samuel, A. L. 1959. "Some studies in machine learning using the game of checkers." *IBM Journal of research and development* 3 (3):210-229.
Sunstein, C. R. 2013. Nudges. gov: Behavioral economics and regulation. Forthcoming, Oxford Handbook of Behavioral Economics and the Law (Eyal Zamir and Doron Teichman eds.). DOI: 10.2139/ssrn.2220022.
Swanson, Z., G. Durler, and W. Remington. 2007. "How do firms address multiple taxonomy issues?" In *New Dimensions of Business Reporting and XBRL*. London: Springer, 127-146.
Thietart, R. A. 2001. *Doing management research: A comprehensive guide*. London: SAGE Publications.

Tinker, A. M., B. D. Merino, and M. D. Neimark. 1982. "The normative origins of positive theories: ideology and accounting thought." *Accounting, Organizations and Society* 7 (2):167-200.

Todorov, A. 2005. "Inferences of competence from faces predict election outcomes." *Science* 308 (5728): 1623-1626. Doi: 10.1126/science.1110589.

Zhang, Y., Y. Chen, W. Luo, J. Zhang, and D. Wang. 2018. Game analysis of XBRL taxonomy extension. *Cluster Computing*:1-10. DOI: 10.1007/s10586-017-1680-z.