Digital Transformation in Asset Management: A Taxonomy Approach

Masterarbeit

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1 Introduction

The capital market has undergone massive changes in the past three decades. One of the most striking statistics to underline this statement is the development of the trading volume of stocks, which has increased from six trillion US-Dollar (USD) in 1990 to 120 trillion USD in 2019 (Statista 2020a; Appendix A). In order to find an appropriate explanation for this massive growth in trading volume, another noticeable statistic clearly points to one of the most revolutionary inventions in the modern world: During the same period (1990 to 2019), the average holding time of stocks halved from 1.6 years to 0.8 years (Statista 2020b; Appendix A). While the characteristics of stocks have never changed, the only possible reason for this development is the trading process. Buying and selling stocks has become much easier since the invention of the internet.

Disruptions create new opportunities and thereby bring new players onto the market who try to capitalise on them. Accordingly, this paper focuses on Robo-Advisors which aim to revolutionize the asset management business by fully automating the entire advising process (Jung et al. 2018a). In 2021, assets under management in the segment of Robo-Advisory are expected to reach 1.3 trillion USD. From 2021 to 2025, assets under management are projected to grow at an annual growth rate of 20%, resulting in a to a total amount of assets under management of 2.8 trillion USD in 2025 (Statista 2020c). These projections show the massive growth expectations of Robo-Advisory (Carey 2019). However, as the future is never exactly predictable, previous growth expectations from the past provide some interesting information about the actual development of Robo-Advisors. KPMG projected in 2016 that assets under management would be 2.2 trillion USD in 2020 (Carey 2019). In fact, the actual amount of assets under management in 2020 was considerably less than 1 trillion USD (Carey 2019). Obviously, the statistic raises questions about the real potential of Robo-Advisory. In order to be able to assess this potential adequately, researchers start to develop a holistic understanding of the functioning and the applications of Robo-Advisory. Gomber et al. (2018) define Robo-Advisors as follows: *"Robo-Advisors enable automated acquisition of information and data processing to provide investment proposals with little or no human intervention based on predefined parameters of customers' investment goals, financial background, and aversion to risk".* To date, Robo-Advisory has not been extensively researched. Accordingly, the analysis and description of objects is currently predominant (Maedche et al. 2019). Existing research articles focus on the design of the working procedure of Robo-Advisory and the digitalization of the advisory process in general (Jung et al. 2018a; Jung et al. 2018b). For example, Beketov et al. (2018) examined the portfolio management methods inside the Robo-

Advisors and Belanche et al. (2019) determined several key drivers of user's intention to use them.
Future growth of Robo-Advisory in terms of assets under management will crucially depend on customer acceptance of Robo-Advisors. Only when customers trust their advisor, more customers can be attracted (Belanche et al. 2019). Even though the field of Robo-Advisory is still not researched extensively, several studies, like Belanche et al. (2019) and Lourenco et al. (2020), have already identified several important factors that determine the acceptance of Robo-Advisory. However, Morana et al. (2020) state that the design of the interaction between users and Robo-Advisors, which certainly is one of the most disruptive characteristics of Robo-Advisors, has only scarcely been researched to date. The significance of this topic is explained next.
Robo-Advisors aim to replace the traditional human-to-human interaction with a human-to-computer interaction (Jung et al. 2018b). Dependent on the design of the human-computer interaction, this can have significant effects on the acceptance of Robo-Advisory (Morana et al. 2020). This paper develops a detailed overview of human-computer interaction characteristics of Robo-Advisors. Consequently, this paper aims to fill the research gap identified by Morana et al. (2020) and to improve the understanding of Robo-Advisory. The design of the interaction between users and Robo-Advisors is of particular importance, because it clearly separates Robo-Advisory from any other type of financial advisors (Jung et al. 2018b). In addition, the interaction may have a significant effect on trust-building, which is, according to Lee et al. (2018), massively influencing the adoption of Robo-Advisors.
This paper contributes to the literature by developing a taxonomy for the human-computer interaction characteristics of Robo-Advisors. This taxonomy and its subsequent analysis directly address the research gap identified by Morana et al. (2020). The research results of this paper will be used by future researchers as well as by developers and customers of Robo-Advisors to identify relevant acceptance factors, to review and expand existing human-computer interaction characteristics of Robo-Advisors and to check if the offered human-computer interaction characteristics are sufficient in order to use a Robo-Advisor. Accordingly, this study is based on answering the following research questions:

How can Robo-Advisors be classified with regard to their human-computer interaction design?

Which archetypes of Robo-Advisors can be empirically identified considering their design of the interaction between users and robots?

The remainder of this paper is structured as follows: chapter two provides a theoretical framework that focuses on digital transformation in general as well as on the role that Robo-Advisors play in this context. It also includes the emergence and the functioning of Robo-Advisors and explains the research gap in more detail. Then, an extensive literature review is conducted which focuses on the identification of articles that are related to human-computer interaction. Those articles are intended to be used in the taxonomy which is developed in chapter four. After the development of the taxonomy, chapter five evaluates the taxonomy by applying a large set of real-world Robo-Advisors to the taxonomy. The resulting distribution is analysed afterwards. Further, this distribution is used to derive a set of archetypes in chapter 5.2. Chapter six summarizes and discusses the findings and also takes relevant literature into account. Afterwards, implications for research and practice will be formulated, followed by a critical review with regard to the limitations of this paper. Finally, the last chapter summarizes the most important findings of this paper.

2 Theoretical Framework

2.1 Digital Transformation in Financial Markets

This chapter uses a top-down approach in order to explain the big picture of digital transformation and the evolution of financial markets which Robo-Advisory emerged from. In order to be able to fully understand the theoretical background of Robo-Advisory, it is necessary to identify the underlying trend that drives constant change not only in asset management, but basically in business and private life. Therefore, this chapter defines and explains digital transformation in general. Afterwards, the focus will be on the implications and consequences of digital transformation for the financial sector. The evolution of new financial technologies will be described and explained, one of which is Robo-Advisory.
Westerman et al. (2014) define digital transformation as follows: *"Digital transformation - the use of technology to radically improve performance"* of organizations and people in their business and private life. Therefore, digital transformation intimately relies on the intersection of technology, people and organizations, which as a whole represents the digital transformation triangle introduced by Imerman & Fabozzi (2020) (see Figure 1). Westerman et al. (2014) assume that technology changes faster than people and organizations. Therefore, people and organizations are challenged by the rapidly evolving technological environment (Westerman et al. 2014). In order for a digital transformation to get implemented and accepted by people and organizations, it is a key

9 Conclusion

The research of this paper was originally motivated by the research gaps that were already outlined in the introduction. The clearest statement comes from Morana et al. (2020) who criticise the scarcity of research on the interaction between users and Robo-Advisors. Based on the statement by Morana et al. (2020), this paper developed its research focus to fill the research gap with relevant results. Two corresponding research questions were introduced. In the following, this conclusion will provide short answers to each research question. These answers will specify the most important research contributions of this paper.

How can Robo-Advisors be classified with regard to their human-computer interaction design?

The first research question was answered by the development of a comprehensive taxonomy with the taxonomy development method from Nickerson et al. (2013). The iterative taxonomy development process, consisting of conceptual-to-empirical and empirical-to-conceptual approaches, revealed four important perspectives for the classification of human-computer interaction characteristics of Robo-Advisors. For each perspective, the taxonomy development method revealed several dimensions and characteristics. The final taxonomy revealed a classification of the human-computer interaction characteristics of Robo-Advisors. This taxonomy contributes to existing research by providing a comprehensive overview of human-computer interaction characteristics of Robo-Advisors, which previous research has not done. Also, it can be revised and expanded by future research. Future research can also use the developed taxonomy to determine and test several factors that could be relevant for the acceptance of Robo-Advisors.

Which archetypes of Robo-Advisors can be empirically identified considering their design of the interaction between users and robots?

The second research question builds up on the developed taxonomy and classifies 57 real-world Robo-Advisors into the taxonomy. The resulting taxonomy distribution of Robo-Advisors is then used to empirically derive an appropriate set of archetypes. The empirical examination resulted in the identification of three archetypes. Thereby, it was striking that many Robo-Advisors have similar characteristics in many dimensions of the taxonomy (e.g., *'Functional'* perspective), which leaves the question whether future Robo-Advisors should seek for more differentiation from their competitors. Furthermore, the empirical analysis showed that Robo-Advisors mostly differentiate from other Robo-Advisors by their usage of anthropomorphic design features.

These are the results of the first paper that has extensively investigated the interaction between users and Robo-Advisors by developing an extensive taxonomy. As it is repetitively mentioned during this paper, these results leave many opportunities for future research. The results can be the basis which future research builds up on. Future examinations in this specific area can use the research results of this paper to clarify the importance of human-computer interaction characteristics of Robo-Advisors for their acceptance by customers.