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TOWARDS DESIGNING ROBO-ADVISORY TO PROMOTE CONSENSUS-EFFICIENT GROUP DECISION-MAKING IN NEW TYPES OF ECONOMIC SCENARIOS

Research in Progress

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Abstract

Robo-advisors are a new type of FinTech increasingly used by millennials in place of traditional financial advice. Building on artificial intelligence, robo-advisors provide personalized asset and wealth management services. Their application and study have hitherto focused exclusively on individual advisory regarding asset management. We observe a pressing need to investigate robo-advisors' application for complex artificial intelligence based recommendation tasks both, in context of group decision-making and in contexts beyond asset management, due to robo-advisors' potential as a lever for integrating artificial intelligence in the entire decision-making process. Thus, we present a action design research in progress aimed at designing such a robo-advisor. More specifically, this study investigates whether and how robo-advisory promotes consensus-efficient group decision-making in new types of economic scenarios (after-sales). Based on a comprehensive problem formulation, we aim towards deriving a set of meta-requirements and design principles that are embodied in a preliminary prototypical instantiation of a robo-advisor.

Keywords: Robo-Advisory, Artificial Intelligence, Group Decision-Making, Consensus Efficiency, Group Recommender Systems, Action Design Research.

1 Introduction

Organizations in different industry sectors and domains increasingly exploit the disruptive potential of artificial intelligence (AI) in their information systems to increase efficiency and effectiveness (e.g., Duan et al., 2019; Griva et al., 2022) and to promote better decision-making (e.g., Agrawal et al., 2017; Wilson, J., & Daugherty, P. R:, 2018; Power et al., 2019; Metcalf et al., 2019; Lam et al., 2019; Dwivedi et al., 2021). This is also reflected by the rise of robo-advisory in financial planning. Robo-advisory has recently attracted information systems researchers' attention, given its potential to harness robo-advisors for leveraging AI in information systems for complex AI-based recommendations tasks (e.g., Beck, 2021; Wexler and Oberlander, 2021). Robo-advisors are built on AI and interactive and intelligent information technology and represent a recent type of FinTech in the financial sector, that offer automated financial investment advisory to individual decision makers (Jung et al., 2018a). This new type of FinTech brings many benefits, e.g., several studies indicate that robo-advisors outperform expert decision-making in financial advisory (e.g., Reher and Sun, 2016; Harvey et al., 2017; D'Acunto et al., 2019; Reher and Sun, 2020) and therefore offer great potential to improve private household's and organizations' wealth management (Jung et al., 2019). Robo-advisors elicit investors' information primarily via online questionnaires and derive a personalized investment portfolio allocation, which is not only implemented but also maintained (Jung et al., 2018b). This illustrates robo-advisors' emphasis on supporting a holistic decision-making process, ranging from the screening of environmental information, creating and analyzing decision alternatives, (supporting) the decision-making, and implementing as well as maintaining decisions (Simon, 1969; Cao et al., 2021).

A closer look at the robo-advisor market and research reveals that researchers focus on the design of more sophisticated robo-advisors that realize greater individualization of automated advice (Torno et al., 2021). However, to the best of our knowledge, no studies have examined alternative contexts beyond asset and wealth management, e.g., complex recommendation contexts such as travel (e.g., Ricci et al., 2022a), food and health (e.g., Elsweiler et al., 2022), fashion (e.g., Jaradat et al., 2022), or economic decision-making scenarios in the business context, in which decision-making support can be implemented by means of robo-advisory. Moreover, research studies and practical implementations haven't considered robo-advisor design targeted toward group decision-making (GDM) endeavors and towards collaborative settings, which is the case, e.g., for some households, where the decision-making process is carried out by two or more decision makers. Similarly, since robo-advisors may not only substitute but augment financial human advisors in financial advisory settings (Salo and Haapio, 2017; Coombs and Redman, 2018; Rühr et al., 2019; Metzler et al., 2022; Beytell and Kroeze, 2022), robo-advisor design targeted for collaborative settings in organizations remains underresearched as well.

While robo-advisors are of interest to various research disciplines, such as behavioral science (e.g., Bhatia et al., 2020) or design science (e.g., Jung et al., 2018b), there is a huge potential in the field of information systems research and in particular in the context of GDM and collaboration. More specifically, we contend that robo-advisors may be deployed both, in alternative application domains to support experts in complex decision-making process and in scenarios involving different stakeholders within an organization (cf. Adomavicius and Tuzhilin, 2005; Rühr, 2020). Robo-advisory may help to overcome the pressing need for "significant extensions" as well as "more advanced recommendation methods" concerning the recommendation modeling and processes (Adomavicius and Tuzhilin, 2005, p. 742-743). This is in line with further research on knowledge-based recommender systems (Felfernig and Burke, 2008) (e.g., Burke, 2000) (Mandl et al., 2011) that argue that robo-advisors are useful for more complex recommendations, e.g. in contexts of financial services (e.g., Felfernig et al., 1999; Felfernig and Kiener, 2005; Felfernig et al., 2007). As a consequence, we see great potential in robo-advisors to enhance capabilities of (group) recommender systems similar to how they have overcome the limitations of practical use of recommender systems in investment contexts (e.g., Lu and Mooney, 1989; Dugdale, 1996; Duan et al., 2019). We further postulate that digitalization stages of robo-advisors can be pushed forward by the integration of AI in tasks beyond the acquisition of user information with dialog systems, or the portfolio selection with recommendation systems (Xing et al., 2019), or the monitoring and automated portfolio rebalancing (Horn and Oehler, 2020). Thus, robo-advisors might represent the emergence of a new class of systems that facilitates the digitalization and AI-based support of holistic organizational decision-making processes in organizational GDM settings.

Since successful AI-advised decision-making is determined by the correct decision, i.e., the consensus in a group setting, on following the robo-advice or not (Bansal et al., 2019), it remains crucial to gain insights on optimal robo-advisor design that promotes consensus-efficient GDM, e.g., by fostering a shared understanding (Suchman, 2007; Bittner and Leimeister, 2014) interactive accomplishments (Engestrom, 1992) or sensemaking (Weick, 1993). This is also reflected in present research studies on group recommender systems (e.g., Roberto, 2005; Ben-Arieh and Chen, 2006; Martinez and Montero, 2007), and is referred to under the notion of *consensus efficiency*, i.e., the "optimal use of resources or correct decisional procedure" (Zhang et al., 2019, p. 580). Accordingly, Bartlett and McCarley, 2019 suggest that research on "human-machine teams" provides insights on future design of robo-advisors, concerning efficient human-automation interaction for decision-making. The literature stream evolving around around AI-advised decision-making (Tan et al; Bansal et al., 2019; Zhang et al., 2020), where "a user takes action recommendations from an AI partner for solving a complex task" (Bansal et al., 2019, p. 2429) underlines, that ideal combinations of humans and machine-learned models, can indeed allow to significantly "improve performance" i.e., decision-making (Kamar et al; Wang et al., 2016). But the design knowledge on effective IT-supported group decision-making and team collaboration is lacking when AI comes into play (Seeber et al., 2020). The depicted need for a better understanding of AI as a teammate or in team collaboration for design purposes is reflected in current information systems research, as evidenced by current information systems research (Seeber et al., 2020; Anthony et al., 2023) and special issues on human-AI teaming in MDPI. To better understand how AI-based robo-advisors can be designed to support GDM and human-AI collaboration, we question how the application of robo-advisors for economic GDM must be designed to promote consensus-efficient GDM. We aim to explore this in more detail in this research endeavor in contexts beyond asset and wealth management, and argue that insights can be transferred to other contexts. Therefor, we focus on the following research question: *What design principles for robo-advisors promote consensus-efficient group decision-making?*

To answer this question, we propose an action design research (ADR) project (Sein et al., 2011), that will be outlined in this contribution. Thereby we want to identify meta-requirements and derive design principles for robo-advisory design that promotes consensus-efficient advisory processes.

The robo-advisor will be deployed in an economic GDM scenario in an after-sales department of a German car manufacturer, where stakeholders from different departments within an organization collaborate to reach the goal of identifying adequate field measures for specific product malfunctions. The robo-advisor supports the collaborative preparation of the basis for decision-making i.e., in terms of the collection, analysis, and evaluation of reliability and field data as well as the performance of other analyses such as cost and vehicle volume analyses. Furthermore, the robo-advisor supports the actual decisions on field measures, by providing AI-based recommendations on field measure design based on the (generated) data and insights generated related to a quality topic.

This ADR project offers insights into specifics of GDM (Chen et al., 2013) and by contextualizing robo-advisors in areas other than wealth and asset management, and into group recommender systems for more complex and rather atypical recommendation tasks (Ricci et al., 2022a). We contribute to the design knowledge base by deriving design principles for consensus-efficient robo-advisors that support GDM (Duan et al., 2019; Dwivedi et al., 2021). Thus the insights obtained will serve towards designing next generations of recommender systems (Adomavicius and Tuzhilin, 2005).

2 Theoretical Foundation and Related Work

2.1 AI-based Group Decision-Making and Support

Research on decision-making theories differentiates between different decision-making formalizations and conceptualizations (e.g., Dastani et al., 2005). In our study we characterize decision-making as identifying a sound alternative out of a set of choices, due to its overall performance with respect to several pertinent criteria. A prevalent decision-making theory**,** that is related with AI-based decision-making, is Simon’s (1977) enhanced process model of decision-making, covering the intelligence (i.e., screening of environmental information), design (i.e., creation and analysis of decision alternatives), choice (i.e., the decision-making), and (the decision) implementation phase (Simon, 1969; Cao et al., 2021). This holistic and most commonly referenced decision-making framework guides the consideration of relevant decision-making aspects in context with AI-adviced decisions and the conxeptualization of solutions for a holistic decision-support, as provided by robo-advisory. In this research endeavor we are interested in economic decision-making problems, that are characterized by a problem situation that calls for a collective solution, being derived by a group of experts who provide their opinions on alternatives (Dong and Xu, 2016). We look at the AI-based support and not the replacement of decision-makers in decision-making processes (Edwards, 1992) and focus on the role of AI as an expert consultant, as it is classified in an early study by Bader et al. (1988), who differentiates AI roles as an *assistant*, *critic*, *second opinion*, *expert consultant*, *tutor*, and *automaton*. More specifically, we look at GDM problems, where recommendations provided aim at supporting the decision makers, i.e., experts, in their GDM process.

Although consensus may not be mandatory for solutions to GDM problems, research reveals that it is a major research area in GDM (e.g., Javier, 1987; Herrera et al., 1996; Ephrati and Rosenschein, 1996; Bordogna et al., 1997; Herrera et al., 1997; Karacapilidis and Pappis, 1997). It “is defined as a state of mutual agreement among individuals of a group, where all opinions have been heard and addressed to the satisfaction of the group" (Dong and Xu, 2016, p. vi). Usually, in real GDM situations that involve different experts, finding an alternative with sufficient consensus is achieved by means of a soft consensus degree, as opposed to hard consensus, which aims at unanimity (e.g., Kacprzyk et al., 1997; Herrera-Viedma et al., 2002). Consensus-reaching GDM process designs promotes the achievement of a sufficient consensus degree for problem resolutions (e.g., Kacprzyk and Fedrizzi, 1988; Kacprzyk et al., 1992; Herrera et al., 1996). Yet present research studies suggest consensus-efficiency to be a prevalent criterion for GDM processes. Here, the emphasis is placed on the "optimal use of resources or correct decisional procedure" (Zhang et al., 2019,p. 580). Next to consensus-efficient processes, other GDM challenges have to be considered when designing GDM processes, like biases in GDM (e.g., Felfernig et al., 2018) as well as personality, emotions, and group dynamics (e.g., Recio-Garcia et al., 2009; Tkalcic et al., 2018; Abolghasemi et al., 2022). Research on recommendation models for GDM that address cognitive and psychological aspects remains scarce.

As the problem situation itself affects and determines the GDM process and its structure (e.g., Gladwell; Klein, 2008) expert GDM can be differentiated between "quick and intuitive, and slow and reasoned", as pointed out by Cao et al. (2021, p. 2). AI potential in GDM situations is rather seen in complex situations that would require slow and reasoned GDM processes (Jarrahi, 2018), characterized by "system two" thinking processes (Kahneman and Patrick, 2011, p. 16) and in need of "competent" IS support (Dreyfus and Dreyfus, 2005, p. 788).

2.2 Group Recommender Systems and Agents

Group recommender systems aim to provide a set of items to a group based on individual preferences or interactions and relationships among the group members (e.g., Barzegar, Nozari, Reza and Koohi, 2020; Abolghasemi et al., 2022; Guo et al., 2022). In expert decision-making processes, group recommender systems provide effective means of coping with the prevailing information overload caused by multi-criteria decision factors (e.g., Kim et al., 2010; Yuan et al., 2014). The group recommender systems distinctions are characterized by the different approaches to their implementation: collaborative (recommendation generation based on users rating profiles, e.g., Goldberg et al., 1992; Resnick et al., 1994; Hill et al., 1995; Sarwar et al., 2001; Herlocker et al., 2004; Smyth et al., 2005, content-based (recommendation generation based on features associated with items and individual user rating profile, e.g., Jennings and Higuchi, 1993; Pazzani et al., 1996; Pazzani and Billsus, 1997; Chen and Sycara, 1998) 21, demographic (recommendation generation based on users demographic profile(s), e.g., Krulwich, 1997; Pazzani, 1999), knowledge-based (recommendation generation based on user needs and preferences, Burke, 1999; e.g., Schmitt and Bergmann, 1999; Burke, 2000; Jiang et al., 2005; Felfernig and Kiener, 2005), and hybrid (e.g., Burke, 2007; Yuan et al., 2014).

The limited practical use of earlier forms of recommendation systems in the context of wealth and asset management (i.e. property; Lu and Mooney, 1989; Dugdale, 1996) underline the shortcomings of group recommender systems as "competent" IS support for complex financial decision-making (Duan et al., 2019). The complex decision-making processes in multicriteria decision-making problems require support at all decision-making phases, not only at the intelligent and design phase, as considered by the prevalent group recommender systems research (Power et al., 2019) but also regarding the choice and implementation phase in the decision-making process. The robo-advisor conceptualization instead provides holistic support in every of the digitized GDM process phases (e.g., Jung et al., 2018a; Jung et al., 2019; Rühr, 2020).

2.3 Robo-Advisory for Financial Decision-Making

Robo-advisors are perceived as part of the modern zeitgeist by investors (Hastenteufel and Ganster, 2021), as they offer automated financial investment advisory (Jung et al., 2018a). The three step automated investment advisory process comprises the traditional interactive advisory process (Jung et al., 2018a; Jung et al., 2019), and can be embedded within Simon's (1977) enhanced process of decision-making, as depicted in figure one. Compared to recommender systems, robo-advisors digitalize the entire decision-making process, instead of merely providing recommendations (Xiao and Benbasat, 2007).

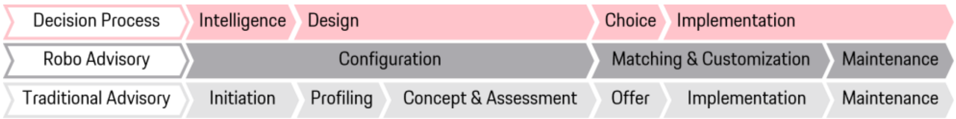

Figure 1. *Robo-advisory process phases* (Jung et al., 2018a; Jung et al., 2019)

Robo-advisors promise many potential benefits, such as professional advisory services for a wide range of users and applications, including financial planning for less wealthy individuals (Jung et al., 2018b; e.g., Fulk et al., 2018) or lay investors who represent financial subjects with little or no investing knowledge or experience (e.g., Glaser et al., 2018; D'Hondt et al., 2020). Whereas Jung et al. (2018a) differentiate robo-advisor research focus into behavior (understanding of the robo-advisor process) and interface design (understanding the robo-advisor as an interface to new investors) Torno et al. (2021) identifies research areas based on a structured literature review referring to the users (addressing user demographics and factors influencing robo-advisor adoption and reliance), the service (process, overall robo-advisor design as well as product characteristics), and the competition area (changes in the robo advisory service). A closer look on robo-advisor research reveals that the question how robo-advisors can support GDM instead of individual decisions and application contexts other then asset and wealth management has yet to be answered.

3 Research Approach and Methodology

3.1 Technical Warranty Extension

We consider the economic decision-making scenario in an after-sales department of a German car manufacturer as our empirical context. More specifically, we look at GDM processes that are characterized by a complex multicriteria decision problem, involving experts from different domains who select field measures that are issued in case of product malfunctions. A technical warranty extension (TWE) represents one of many field measures reasonable in case of product malfunctions. Experts deciding in favor of the extension of a technical warranty on a specific component or system for a specific term, beyond the new-car warranty conditions, are primarily driven by the intension to ensure customer satisfaction. Alternative measures to the TWE are workshop or recall campaigns, but these are rather aimed at granting product safety instead of retaining customer satisfaction. Decisions in favor or against a TWE are based on a sound analysis of the data basis for various criteria, such as legal aspects, the component and system reliability, the term of the TWE and associated cost development forecasts and require the involvement of various stakeholders, who examine the different aspects of the decision and bring individual perspectives on the issue to the GDM process. Decisions on TWEs need to be implemented, monitored and eventually maintained, since changes related to the quality issue may affect customer safety or satisfaction, as well as other decision related aspects like cost developments, what calls for an digitalization and support of the entire decision-making process.

3.2 Research design

In our study, we aim to answer our research question by designing a robo-advisor for the TWE-management, named TWE-advisor. Therein we consider the ADR methodology (Sein et al., 2011) derived from design research (Hevner et al., 2004; Hevner, 2007). The methodology is particularly suitable for research environments which „require repeated intervention in organizations to establish the in-depth understanding of the artifact-context relationship" (Sein et al., 2011, p. 53), as it is the case for knowledge based recommender systems, that are relevant to our empirical context.

To ensure that the design knowledge is developed in a comprehensible, i.e., empirical, manner, it will be triangulated (Creswell and Miller, 2000; Creswell and Poth, 2016) out of insights from several scientific methods, that are allocated in our research design in figure two.

Stages	Principles	Methodologies	Artifact
Stage 1: **Problem Formulation**	Principle 1: Practice Inspired Research	Requirement Engineering: Document Analysis, Focus Groups (Interviews, Object Analysis, User-Stories)	**Recognition**; Problem Formulation, Learning Goals and Objectives
	Principle 2: Theory-Ingrained Artifact	Litrature Research	
Stage 2: **Building, Intervention & Evaluation (BIE)**	Principle 3: Reciprocal Shaping	Prototyping	**Alpha Version**: In the alpha version of the evaluation, ex ante, problem identification and artifact design are highlighted. Design Assumptions
	Principle 4: Mutually Influential Roles		
	Principle 5: Authentic & Concurrent Evaluation	Ex-ante/post Expert Interviews	**Beta version**: ex-post evaluation delves into the applicability and value of the artifact. Revised Design Principles
Stage 3: **Reflection & Learning**	Principle 6: Guided Emergence		**Emerging Ensemble & Realization**: Design Decisions
Stage 4: **Formulation of Learning**	Principle 7: Generalized Outcomes	Workshops	**Ensemble Version**: Instantiation embodying design principles and managerial implications

Figure 2. Research design (Sein et al., 2011, p. 51)

For our research design considerations, we will follow the organization-dominant schema, as depicted in figure three. In the organization-dominant schema (Sein et al., 2011), end-users, i.e. experts, are challenged early about the artifacts' design, as compared to the IT-dominant schema. We plan to conduct two ADR cycles, in which both the alpha version and the beta version of the design artefact TWE-Advisor are being prototyped. In the first design cycle, assumptions about the meta-requirements and design principles will be derived, and later refined in the second design cycle. Practitioners involved in the ADR-project are both data scientists and analysts from the Business Intelligence Competence Center in the after-sales domain. Whereas experts, i.e., end-users, are represented primarily by experienced domain experts from the after sales department who participated in the GDM process for field measures for many years, while secondary representation of experts comprises stakeholder groups from various enterprise divisions such as production or procurement.

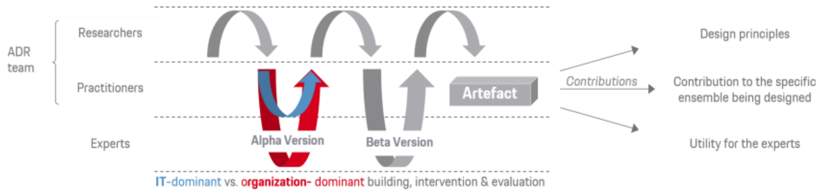

Figure 3. Organization-dominant building, intervention & evaluation (Sein et al., 2011, p. 42-43)

After outlining the ADR research design, that serves to answer the research question, the contribution at hand further depicts considerations concerning stage one as well as related intermediate results in section four that will serve as basis for the subsequent stages planned for this ADR research project.

3.3 Stage 1 : Problem Formulation

The purpose of the first stage in the initial ADR cycle is to outline a practice-inspired and theoretically derived problem formulation. Here, we aim at obtaining expert-stories that are contextualized with identified kernel theories and justificatory knowledge. This serves as a basis to derive meta-requirements and design principles in the next stage of the first ADR cycle. Figure two depicts the stage's interrelation to other stages; the insights and results obtained in the first stage may be influenced and renewed due to insights and results obtained in upfollowing stages. This is explained in more detail in the following.

To ensure the protoypization of a theory ingrained artifact and to become familiar with the reference discipline and the scientific contributions to the research area, a structured literature review on the basis of the guidelines of Kitchenham and Charters (2007) will be performed. By means of the structured literature review, we aim on identifying kernel theories and justificatory knowledge, that serve for the contextualization of expert stories. In the present planning phase of the structured literature review, we use the sample of primary identified studies to develop our review protocol and data extraction form, that will guide the subsequent conducting and reporting phase of the structured literature review (Kitchenham and Charters, 2007), where the identified relevant kernel theories and justificatory knowledge are documented and give insights on different aspects, e.g., on how to determine and measure consensus-efficiency. We derived a sample of primary literature that was considered to initialize the problem formulation, as outlined in the introduction of this paper, based on an initial search process, using the title comparison function of the Google Scholar metasearch engine and considering the search strings robo-advisory design, group decision-making, consensus-efficiency, group recommender systems, as well as backward and forward search.

To ensure practice inspired research, we consider document analysis (Burge; Khan et al., 2014) and iterative requirements engineering workshops (Goguen and Linde, 1993; Paetsch et al., 2003) as good techniques to derive expert stories on the problem and on requirements for an adeguate information system solution. In our three part requirements engineering workshops, we conducted semi-structured interviews in the first part, to comprehend the problem domain (Goguen and Linde, 1993). In the second part object analyses were performed, by means of entity-relationship-diagrams, for task and process specification related to the different stakeholder groups (Dick et al., 2017). In the third part user-stories, i.e. expert stories, were formalized by means of following template structure: *'I as [function] want [x] in order to [x]'* (Dick et al., 2017). As of now 28 Workshops with seven different stakeholder groups consisting out of two up to ten people were conducted, what led to over 120 expert stories.

The expert stories and requirements elicited in stage one inform the prototype development in stage two. Thus, we considered initial expert-stories from the problem domain and look at the solution domain, by initializing the prototypization of a first version of a web-based system, i.e., the TWE-Advisor (Paetsch et al., 2003), that represents the prevalent outcome of this preliminary work and will be referred to as prototypical instantiation in the subsequent section.

4 Conceptualization and Instantiation

We started the first design cycle of our ADR research project by performing the planning phase of the structured literature review as well as requirement workshops to identify and contextualize kernel theories, justificatory knowledge and expert stories. These serve as a basis to establish meta-requirements and derive design principles that will be mapped in a diagram as proposed by Möller et al. (2020) in order to visualize the transfer of empirical insights into design principles and design decisions (Haki and Legner, 2013) as visualized in figure four.

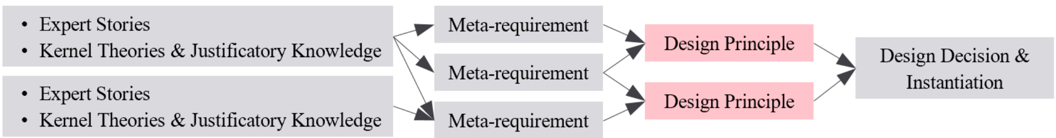

Figure 4. Meta-requirements and design principles construction as mapping diagram

The instantiation of the design principles is achieved, by prototyping a web-based system for the robo-advisor, i.e., the TWE-advisor, that digitalizes a consensus-efficient GDM process and performs complex recommendation tasks. More precise, the TWE-Advisor, will digitalize and support the four different phases of Simon's (1977) decision-making process for decisions about issuing TWE's in line with the typical robo-advisory phases, e.g., the TWE-advisor supports experts in identifying whether a specific components or systems, that incur malfunctions, describe "conditions calling for decision" about issuing a TWE as a field measure or not in the initiation phase (Simon, 1960, p. 2) or the robo-advisor will support the "detection of contextual changes that are significant to the user and therefore justify a recommendation" in the last phase, i.e., the maintenance phase (Ricci et al., 2022b). Figure five depicts a conceptual prototype (mockup) of the TWE-Advisor, that is offering advice on TWE issuance.

To date the TWE-Advisor mockups are deployed as first version within the web-based system and they serve as inspiration and discussion basis for the expert-stories refinement in stage one.

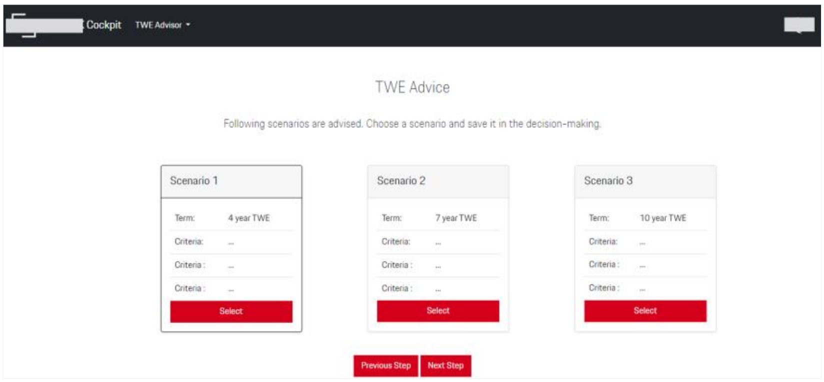

Figure 5. Screenshot of the current version of TWE-Advisor (Illustration of the offer-phase)

As underlined before, the TWE-advisor support goes beyond a recommendation in the choice phase and GDM support along all decision-making phases will be provided.

5 Conclusion and Outlook

In this research in progress paper, we present and outline the approach as well as the intermediate results of our ADR research project, in which robo-advisors' potential to enhance capabilities of group recommender systems is being examined. More specifically we are the first to prototype and deploy a robo-advisor in economic decision-making scenarios beyond asset and wealth management and investigate robo-advisory application to holistically support consensus-efficient GDM processes. The envisioned TWE-Advisor, digitalizes the expert decision-making processes in the after-sales context of a German car manufacturer, related to issuing TWEs as field measures for malfunctioning components or systems in the field. The TWE-advisor supports consensus-efficient GDM by guiding the decision makers through all phases of a digitalized decision-making process (Simon, 1977) and by providing recommendations based on AI-generated insights, that are related to the multicriteria factors underlying the decision problem (i.e. risk, cost, failure prediction and assessment). We add to the design knowledge base about information system artefacts, i.e., recommender systems, by identifying and refining meta-requirements and design principles in the subsequent course of our research. Therefore, we plan on finalizing the conducting and reporting phase of our structured literature review as well as the focus group sessions with the identified stakeholder groups in order to contextualize expert stories and kernel theories in stage one. These will guide the building, intervention and evaluation cycles of the TWE advisor prototyping in and serve as a basis to formulize and map meta-requirements and design principles in the subsequent stages of our presented research design.

However, our present work has some limitations that need to be articulated. We in particularly acknowledge the exploratory nature of the present planning phase of our structured literature review, with a certain degree of subjectivity in the identification of primary studies for the creation of the research protocol and extraction form. We expect this limitation to be mitigated by performing and presenting the results of the upcoming conducting and reporting phase of the structured literature review. Concerning future research endeavors we expect further group recommender systems research to benefit from the potential of storing and analyzing GDM processes at a finer level of sub-transactions (e.g., Chen et al., 2013), since we provide insights on a digitized decision-making process analogous to the typical robo-advisor process phases. Further, due to the varying contexts in the GDM domain of our practical use case, we expect to provide a basis for further analyzing and modeling the impact of contextual factors (Chen et al., 2013) (i.e., after sales) in further research endeavors.

To conclude, we believe that considering the robo-advisor design principles for consensus-efficient GDM derived in the context of our ADR project, can significantly augment the capabilities of recommender systems for integrated and complex decision tasks and holistic decision-making support.

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