Responsible and human centric AI-based insurance advisor

Abstract:

In this paper we present novel approach, based on AI, to suggest insurance coverage for users and families. It is not yet fully explored the domain on what does it mean to give responsible and human centric recommendation in the context of AI-based insurance. Therefore, in this article we provide an in-depth analysis on i) specifications and requirements for the system from regulation point of view, ii) instructions on how to design such system and on which data it can rely upon, iii) which recommender techniques can be used for developing such advisor, and finally iv) off-the-shelf components for trustworthy, responsible ethical behavior of this Ai-empowered tool. Solution as proposed in our paper will be transparent, trustworthy, and responsible towards the final users, thus we hope, better accepted by customers. After describing such possible system design and architecture, we discuss critically challenges and opportunities for deployment of such systems in insurance companies.

Keywords: Digital Advice; Product Design; Insurance; Product Innovation; Robo-advice

1. Introduction

The economic literacy of everyday clients of financial institutions is in general low and customers often need financial advice on how to invest their money or on the financial product best suited for them (Van Raaij, 2016). Companies in the past provided financial advice to their customers in different forms, it can be given in person, with face-to-face interaction with a dedicated employee for this, or recently customers can also ask for such advice online (van Thiel et al., 2008). In recent years, there's an especially big debate about the use of intelligent advisors and if such advisors will be accepted by final clients (Dunbar et al., 2016; Frey et al., 2015). These software tools more and more often replace the dedicated advisors employees in the financial institutions. Currently such replacement processes take place in many developed courtiers, and growth of such online recommendation platforms is to be expected (Bradbury et al., 2014).

The way financial advice is given is on the way to be transformed by the process of digital transformation (Malhotra and Malhotra, 2006). Intelligent advisors are online services that help customers make financial decisions specific for their needs (Collins, 2010). As clients demand more clarity of information, providing such information well online becomes increasingly important.

Previous research on digitalization for the financial companies distinguishes three waves or phases of digitalization (Frey & Osborne, 2017; Puschmann, 2017) :

1. Internal digitalization: financial companies digitizing their internal processes, that is coming up and using hardware and software that improves their own processes,
2. Provider-oriented digitization: financial companies focused on integrating standardized solutions by dominant technology providers,
3. Customer-oriented digitization, this phase is centered around customers and the ways how customers interact with the companies, it includes the development of new types of payments, robo-advisors, etc.

Tech aided advice is present in all financial services. One example is an advisor that helps clients with loans or lendings (Zhang & Liu, 2012). This one in particular advises on all different digital types of making capital available. Other advisors support other digital financing categories and digitized services in the areas of crowdfunding or wealth management (Xue et al, 2018; Pompian & Wood, 2006).

Nowadays financial companies collect all kinds of data for their clients and they use them in many different ways, especially in this third generation digitization services example. One of the opportunities lies in exploiting these data in new contexts, as we try to propose in this paper, and to use past data to come up with suggestions for users in their current financial situations. This is additionally fueled by the fast development of AI and machine learning as fields. This data can bring better transparency and accessibility to both, companies and clients, the companies to know everything about the customers, and also the customer can get a more transparent, better explained to them advice, based on similar past data.

It is not simple to build insurance advisors, companies are facing the following challenges when they try to do so and come up with automated ways to give advice. First, the company performs an evaluation of client in terms of family status, possessions, and income. Second, the company needs to understand what are the risks to which the client is exposed. Third, it needs to recommend and give personalized advice on the most suited solution for the client, and finally, should control and monitor to ensure that the client is doing OK and that the company does not lose profits from the given advice (Ben-David & Sade, 2018).

In the beginning, most digital advisors are designed and planned to target only young adults. There is recent literature suggesting that advisors will be specialized and will be personalized to the types of client. The financial needs of a 25-year old and a 60-year old client are different, both in what these advisors need to take into account, and in terms of different user interaction techniques that the software should rely on. Another client type will be the companies or brokers. Here, the digital advice are more complex, as coming up with a quote on the insurance of a company requires that the company enters a long list of parameters needed for the insurance company to come up with a quote, or even further the needs of an insurance broker are even more complex, as they need to compare offers between different insurance agencies (Belanche et al, 2019).

In the sector it is already known that it is important to make the advice personal. Some scholars claim that it is important to make both: current personalized advice digital, and to make future digital solutions personalized (Capponi et al, 2019). The customers value trust in the financial industry more than other other industries. One of the reasons why the digital transformation is slow in the financial industry is because the industry builds on trust, and in particular, clients rely on personalized information from their financial advisor. Thus the lack of trust in insurance advisors is exactly seen as one of the drawbacks of robo-advisors, 72% of the clients believe that automated advice cannot give the best advice as humans can (Gomber et al, 2017).

Literature has also studied digital advisors software that rely on gamification as a strategy (Grgurevic & Stroughair, 2018). Vitality, for instance, tries to keep their clients healthy and helps them exercise by tracing their steps with Fitbit and rewarding the customers with free Starbucks coffee, gym discounts, or movie tickets if they reach the targets that are set to them weekly. This idea builds on the premises of gamification, there are small short-term rewards for improving the overall long-term behaviors. The customers can afford to buy Starbucks coffee on their own, still, the sense of having “won'' something gives a physiological value to push for reaching the goal.

At the same time financial education is increasing. There seems to be an implicit connection between financial literacy and financial behaviors (Kaiser & Menkhoff, 2017), and financial education improves financial welfare (Xiao & O'Neill, 2016). These kinds of findings have implications for financial service professionals and people who design the advisors: they need to take account the different levels of financial literacy of the users and adequately also provide suited information and "educate" their customer base, in addition, they need to design for confidence in knowledge and ability, and empower their customers to take action.

It's important to note that digital advisors must be compliant with regulation and it plays a central part (Ostrowska & Balcerowski, 2020). There has been a great increase in amount of regulation imposed on financial companies due to financial crisis. The adherence to regulation brings also challenges to robo-advisors implementation from technical and process points of view. For big companies the situation with regulation is even more complex as they need to implement compliance with regulation for all the activities they do.

In this paper we focus our investigation on giving advice in insurance as a service, based on AI, that is transparent and trustworthy.

Many customers in the past have reported to not understand the conditions of the insurance contract or have reported that the sold insurance doesn't actually satisfy their needs (Gatzert and Holzmuller, 2012; Diacon and O'Brien, 2002). In addition, due to digital transformation and the big improvement in the quality of services in the other industries across the other industries as well (Uber, Airbnb, just to name a few), push insurance companies to provide easy to understand information to the final customers as well. Therefore, insurance companies are constantly experimenting with new ways to explain their offers well to consumers digitally as well.

In a past publication, we presented a tool to give digital advice to customers of an Italian insurance SME, in this paper we focus on studying how to make the advice more efficient, based not only on personal data entered by the customer, but also on past data and AI, and how to explain this advice, thus make it understandable to the final users, thus increasing acceptance of final users, and contribute to the wider aim on making Ai algorithms more transparent.

The rest of the paper is structured like this: Section 2 sums up insurance advice past work, Section 3 presents sums up regulation and guidelines for development of ethical and trustworthy AI tool in the domain, Section 4 proposes design for an AI based insurance advisor, relevant recommender strategies that can be used, possible architecture and existing widgets and tools insurance companies can use for this aim, Section 5 concludes the paper.

2. Prior work

As part of a prior paper (Pisoni, 2019) we showed the steps the case SME took to develop a tool that based on entering key data information like age, income, presence of a partner that has income, children, it calculates the ideal amount the customers should insure themselves upon, the yearly premium they should pay in order to be insured on that amount and help, and explains better why this amount has been proposed to the user. The aim was to simplify and make more transparent the process of calculation of the amount to insure upon and explain better to the customers why they need such coverage.

For the implementation of the tool and calculations behind it's functioning, the authors used tables provided by the company on the different levels of risk associated with different age, marital, family, job and estate status of the client, and automated what was already a common established practice by the company to do when a client was asking or a life insurance policy advice, and was when evaluating the type of life insurance policy to offer to the clients asking for such quotes. The tool was designed on purpose to be as simple as possible, so that users with different needs can still use and obtain advice and further information for their specific needs

Next, we want to make use of prior company data and AI in our app. However, providing estimations and giving advice with big data and AI brings regulation and ethical complications that need to be properly addressed in the app. The privacy- and security-related consequences in this case are minimal, yet the ethics issues are relevant and important to be considered (Clavell, & Peuvrelle, 2020). There are already tools and approaches that provide explanations to decisions made by ML and AI. For instance, CARLA is a tool that detects and suggests actionable features (e.g., bigger salary) that permit the person to have a positive result in future (e.g., loan approval) (Pawelczyk et al, 2021), or for instance the observatory of algorithms with social impact studies enlists different algorithms and provides information about their aim, therefore aiming to demystify opaque and unaccountable algorithms that have proved to be systematic biased against women and minority groups[1]

Digital Operational Resilience Act (DORA)[2] is a new EU regulation introduced to harmonize digital risk requirements (it's specific for finance), that is being discussed at the time of writing of this article regarding the digital operations of financial institutions. In Singapore, financial authorities came up with principles of fairness, ethics, accountability, and transparency, abbreviated FEAT[3] that AI of financial companies in Singapore must comply with. In Europe such regulation, specifically regarding financial institutions use of AI and ML now is missing, therefore our paper is timely.

In a setting like ours, the use of interactive ML (iML) is a key as well. In the insurance industry, it may be the case that the traditional ML approaches might have limited success, in the case of rare events not available in the training dataset. Interactive ML is approach to ML in which algorithms interact with agents (these agents can be humans too) and thus trough these interactions can be optimize their behavior (Holzinger, 2016), and it is indeed that in some cases iML would need to be adopted.

In this work we study what considerations companies should make when ideating tools based on AI and machine learning and that take as input: data coming from different online purchasing channels, data coming from previous knowledge of insurance companies, and again existing business rules.

Insurance companies need to be compliant with regulation, therefore software built needs to comply with these regulation too, so in this paper we sum up legislation view and he different legislations that insurance companies must be compliant and vigilant about, we suggest which recommender approaches to use (how to design such system, which recommender approaches to use), as well as widgets to use for development of such fair and not biased decision making system (based on e.g., fairness IBM Toolbox and responsible AI widgets)

3. Regulation aspects

New financial directive has been put in place in Europe (MiFID II), regulating financial products and therefore relevant operations, since January 2018. Due to this, also insurance directives were updated to offer the same level of customer protection as in traditional financial instruments.

[1] https://eticasfoundation.org/oasi/register/

[2] https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020PC0595

[3]https://www.mas.gov.sg/~/media/MAS/News%20and%20Publications/Monographs%20and%20Information%20Papers/FEAT%20Principles%20Final.pdf

The sellers of insurance products are also subject to same rules as those that apply to businesses operating in finance. They must keep proof that they have worked in the best interest for the client, need to perform client reporting, and need to be transparent about third party inducements (giving or receiving benefits to third parties to not affect the company ability to act in transparent and ethical way to the client). The regulatory regime is aimed to protect the customer

Most important obligations for insurers are listed below:

- Insurance digital companies need must work in the best interest of the customer and keep track for such behavior, that is in a transparent, ethical, and professional manner to the client

- Transparency, that is regarding the insurance coverage advice given, there must be a full transparency on the obligation in respect to the company (are other companies involved too?, what are the obligations towards them?), and if there are such companies their names and obligations towards them need to be clearly explained, in addition, the nature of the free (renumeration) in relation to the insurance coverage must be clearly outlined

- Explainability of the approach: a suitable explanation must be provided to the client, in the insurance domain is that one of counterfactual explanations (CE), which implies implementations of interventions as input to the model, so that the output changes is in advantage to the client. By providing which feature is important to which recommendation aspect, the CE methods can fall in one of these categories: interdependence-based, dependence-based, and causality-based approaches.

Therefore, for companies it becomes important to:

- Establish, analyze, and constantly update policies and procedures that allow the company to act in the best interest of the customer, that are transparent and based on ethical principles

- Make sure that all adequate information is provided to the customer (fees, benefits and obligations, commissions)

Suitability assessment

The digital insurance company that is about to provide insurance advice, about a life insurance product to the final client, need to be able to assess the fitness of the product for the client, and for this aim the company should collect the following information from the customer

- Prior knowledge of the customer for the specific insurance policy,

- Current financial situation,

- Insurance objectives.

Normally, to ensure these regulatory obligations are met, an insurance company that obtains this information from the customer, should employ suited questionnaires, and ask the customer for evidence for the statements made about the financial situation. In this case, the collection of information being digital, the insurance company needs to keep record of all the information declared by the client. These proof for fitness of the product should be saved by the company.

In addition, the acceptance of rights and responsibilities should be stored, that is that both have been communicated and accepted mutually, by the insurance company and client.

The ‘suitability statement’ produced should be recorded on 'durable medium’. This record should describe the customer preferences as well as how the suggested insurance advice satisfy the criteria, therefore explainability is a strong requirement in this sphere.

A storage of information in 'durable medium' means for the insurance company that, (a) it needs to store the information, and the information needs to be accessible for an upfront decided period, (b) the information stored should be available to be reproduced unchanged.

Appropriateness assessment

If the necessary information is not provided by the client, or current financial situation of client is not adequate for the insurance request, then this answer should be recorded to testify the company worked in best interest for the customer.

4. AI-based insurance advisor

In order to design an AI system that will be able to explain its decision to the final users, first one needs to understand what it means to create a system that provides an explanation for its work in this context and what it means to have explainability and in the frame of AI systems.

To explain an outcome of an AI system, means to produce human understandable description on why the system made the decision, it is composed of three sub steps: i) explaining possible causes for outcome, ii) providing outcome description, and iii) passage of additional context information to the user for understanding and the causes for the outcome.

When we speak about AI, we often speak about interpretability and explainability of AI. Interpretability means providing meaning in understandable way for the user, while explainability is linked with the passage of knowledge and understanding on how decision was made from the decision-maker to the user. These two concepts are interlinked, in this paper we work on discussing explainability, however, we also note the importance of interpretability

Previous literature (Kim, 2018; van Engers & de Vries, 2019; Sovrano et al, 2019) has studies also what are the characteristic of a good recommendation of similar systems in digital finance: external coherence, internal coherence, the explanation needs to be simple, not in contradiction, and easy to “consume”. In addition, good interaction.

An explanation should provide a clarification on how and why the recommendation was made.

4.1 On which data to rely on? How to design such system?

Insurance advise systems must address the problem of “why an advice was made?”, therefore the system should provide, an advice and an explanation on why that precise advice was given, in relation to personal information available or entered.

Such information will increase the transparency and understandability of the system to the final user, nevertheless the users as a result will fell more trust, satisfaction and acceptance.

In Figure 1 we provide a wholistic view on the AI insurance system within the company, while in Figure 3 we present the specifics of the explainable AI component. In the context of insurance company, we discuss about different sources of data, Figure 2 (a) summarizes the different sources of data usually used in insurance context. Figure 2 (b) summarizes a first framework for how such systems should look like (systems as we try to build) adapted for the context of insurance advice from (Gunning & Aha, 2019) and other previous literature on human understandable and explainable AI (Hagras, 2018; Thiebes et al, 2020; Al Ridhawi et al, 2020)

In our case the system provides both, the results of the advisor, and an explanation on why that advice was given.

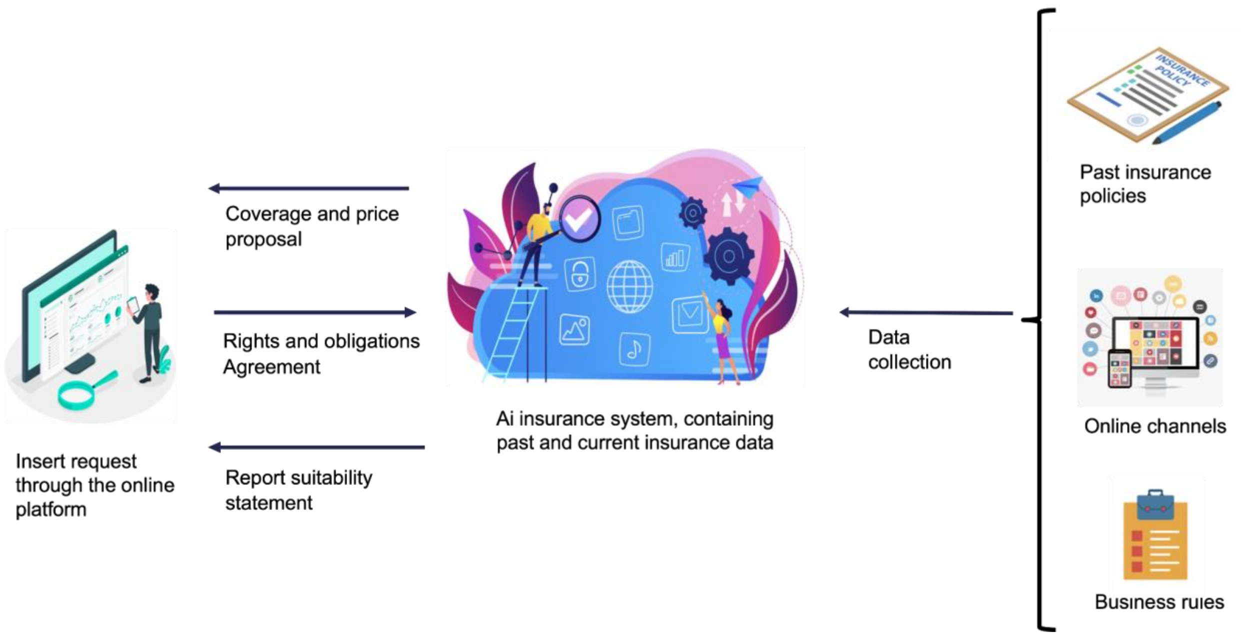

Figure 1. AI insurance system within the company

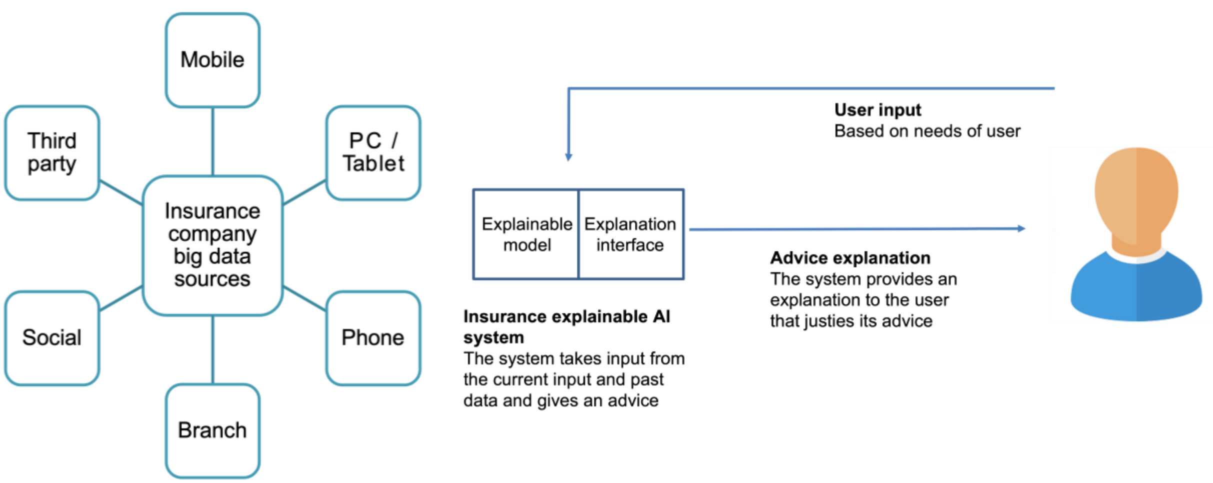

Figure 2. (a) Summarizes the different sources of data usually used in insurance context, (b) summarizes a first framework for how such systems should look like (systems as we try to build) adapted for the context of insurance

advice from (Gunning & Aha, 2019) and other previous literature on human understandable and explainable AI (Hagras, 2018; Thiebes et al, 2020; Al Ridhawi et al, 2020)

4.2 Which recommender system techniques to use?

Previous literature (Alhijawi & Kilani, 2020; Vultureanu-Albişi & Bădică, 2021; Zangerle et al, 2021; Gedikli et al 2014) in the recommender systems analysis different techniques one can use in the context of advice systems, we sum below the most suited for the domain of insurance advice:

- Knowledge-based, collect and use the different types of knowledge for the domain across different data bases of the insurance company (Aggarwal, 2016).

- Content-based, select and use past user interactions to extract past knowledge around similar prior requests and outcomes (Lops, De Gemmis & Semeraro 2011)

- Demographic-based, to derive with an advice, based on the "demographic type" or "stereotypes" on personal attributes of the user (Burke, 2002; Aggarwal, 2016).

For instance, other approaches to recommendation, like collaborative filtering (often used on social media data), or context aware approaches (used in situation where the context is important), we find little suited for this kind of task. Many times, social media interaction is outsourced outside of the insurance company or given to social media specialized companies, which would require further enterprise architectures extensions to connect to those data, and social media data may not be needed for the task. There is a gap in the recommended system literature, regarding responsible and human friendly AI we identify in this with this paper we try to give some first approaches.

4.3 Widgets for development of insurance advise tool

Suitable tools can be built of top of existing insurance enterprise infrastructures. In a prior paper we have discussed new designs of enterprise architectures for insurance as well as their adoption by the industry (Molnár et al, 2020; Pisoni et al, 2021). As insurance companies are businesses focused on the consumers, therefore even traditionally, separated users based on their demographic's attributes and monetary situation, as well as geographical location and sex.

The services and products offer to different groups are not the same, therefore the services are tailored and to satisfy the requirements of different customer segment. In this domain, the clients are not treated equally, and rich customers are offered more services compared to traditional customers. It is especially important to provide to rich customers all the important support, thus the data analysis processes even before intervention as ours are centered around the various target groups, which is only an advantage.

The usually employed data analytics process, also called data analytics pipeline (Molnár et al, 2020; Pisoni et al, 2021), means that the information collected through the various databases of the financial company goes through these 5 phases, data being "Source", data being in stage of "Ingest", "Processing", "Storage", and "Delivery", where information is mined and presented to the insurer. Data from different sources is put in the same format, so to be offer possibilities to be further analyzed, and create new insights for the company.

Data in transformed and the big quantity of data allow for creation of new knowledge of company, and discovery of patterns not obvious before.

In Table 1 we sum up some modules that can be adopted by an operating company for this aim, that is services that can be used by insurance institutions on top of existing data analytic pipelines, to develop such AI based system.

Tool name	By whom	Description
AI Fairness 360	IBM	Group of algorithms, criterias for datasets, and models to check for bias in the data, especially in industrial settings and applications, collecting practices regarding AI fairness from research and industry (Bellamy et al, 2018)
Responsible AI	Microsoft	An open-source toolbox that incorporates other open-source models in the area of interpretability, counterfactual analysis, error analysis, and fairness
Aequitas	University of Chicago	Aequitas is a fairness audit toolbox, with easy integration with existing data analytics pipelines, enables the users to test models in relation to fairness metrics and bias (Saleiro et al, 2018)
Certifai	University of Texas	Model-agnostic framework aimed to generate counterfactual explanations, it provides to the users scores on fairness and robustness, generates explanations as well as predictions on actionable features that can change the outcome of the model (Sharma et al, 2020)
FAT Forensics	Thales / University of Bristol	FAT Forensics is a toolset of models and metrics, supporting users in their machine learning analysis by deliveringmetrics on fairness and accountability of predictions (Sokol et al, 2019)

Table 1. A list of modules that can be adopted by an operating company to analyze big data in ethical and responsible way

5. Discussion and Conclusions

In this paper we discussed how an instance company can automate, based on AI, the process of giving advice on the amount clients should insure themselves, based on big data they have in their possession. For this, the application uses past data from the company to provide such quote, data the company has from other channels for the users, and the clients of the company provide personal demographic information about them and their family, marital status, income, and real estate status as well to provide basic demographics for themselves, and their partners. Our analysis provides hints for future developments of such AI systems in other financial or insurance companies, discusses regulatory compliance, sources of data for development of such systems, possible recommender approaches, already available widgets insurance companies can use for development of such systems. Overall, if implemented well, such an AI system can bring to a more thoughtful and in depth understanding of the insurance policy proposed for the clients and in line with customer needs and based on past data.

The fast adoption of data analytics and use of AI and ML in these settings, makes it important to not only use models that have high accuracy, but that are also able to explain and justify their decisions and advice, it also necessary from GDPR constrains (Karimi et al, 2020). Different guidelines also start to appear regarding ethical application of AI in insurance in Europe, for instance the Europeans insurance and occupational pensions authority (EIOPA) developed six principles to regulate AI use in the insurance sector in Europe and promote ethical and trustworthy use[4]; or for instance (Keller 2020) investigates how to promote responsible use of AI in insurance and focuses on transparency and fairness, something that is indeed difficult to establish in the insurers world[5]. In this paper we focused only on providing explanations, yet, another equally interesting future work can focus on what does it mean and which modules companies can use to provide recommendations to the users. First examples in this direction are provided by (Pawelczyk et al, 2021; Karimi et al, 2020).

Works in this direction are important for creating future-proof insurers in which AI is used safely.

Many future challenges still remain. For instance, previous studies tell that customers may not feel comfortable with their prior data being used (Cheng et al, 2019). This is one of the known limitations of systems like ours and previous research has reported similar findings like us. We believe that this aspect is worth further exploration in various directions; in particular, finding a way to 'collect' such data from past interaction with the company or different use of personal data in ways that are as most anonymized as possible. Another more ambitious futurist direction is to investigate how to integrate data available from other sources (public institutions, other sectors) and to propose amounts on which the customers should insure themselves based on previous existing behaviors of the clients towards incidents insurance, and non-insurance history.

In this context, we work on designing a system in which insurance advice explanation serves to justify advice to the client. One futuristic work, for instance, can also foresee improvement of the explanation proposed, by feeding the AI, with return feedback from the user on how good the advice provided was, so the system can learn from provided feedback from the users on how in line with their needs the given advice was.

We underline several limitations. Our research focused on regulatory aspects and system design, however not on potential deployment problems. Future research must consider different deployment scenarios, deployment models for different enterprise systems used in the sector. Next, experience shows that the use of such approaches is mostly dependent on presence of experts in the company and contextual factors (Kruse et al, 2019, Flavián et al, 2021). Therefore, there is also a need for research that strengthens the understanding of how these tools can be 'institutionalized'. In addition, as developments move quickly in this area, the list of toolboxes and widgets would need to be constantly updated.

In relation to the developments in AI as technology, many other long-term implications are still to considered and answered properly in relation of using AI in services like ours. Future research needs to advance the understanding of how evolving services should be designed, especially in synch with ongoing internall process of companies using such services, and to pave the way both, managers, and policy makers. Our paper is a first attempt and insight into approach that researchers and managers can apply this direction.

In this paper we outline the considerations for the development of an AI-based insurance advisor to provide its customers with some advice on the amount they should insure themselves. Our paper advances the available research in the domain of digital advisors for insurance industry and shows how financial companies can provide more AI-based understandable, transparent way to use data for all, clients and the company, needless to mention, to increase the number of services they offer. The results can be used by

[4]https://www.eiopa.europa.eu/document-library/report/artificial-intelligence-governance-principles-towards-ethical-and_en

[5]https://www.genevaassociation.org/research-topics/new-technologies-and-data/promoting-responsible-artificial-intelligence-insurance

other companies to 1) design solution on their own AI-based insurance advisors, following the processes and guideline principles as outlined in the paper and 2) understand needs and requirements driving the design of such systems.

Our next steps foresee a development of the prototype software tool using data from companies the authors collaborated in the past for this research, as well as enlargements and assistance for other insurance products, not only giving advice for life insurance policy, but also for car and home insurance, domains for which the companies have lots of prior data easy to use. In addition, we try to integrate with other type of data already available online to the extent possible.

REFERENCES

Alhijawi, B., & Kilani, Y. (2020). The recommender system: a survey. *International Journal of Advanced Intelligence Paradigms*, *15*(3), 229-251.

Al Ridhawi, I., Otoum, S., Aloqaily, M., & Boukerche, A. (2020). Generalizing AI: challenges and opportunities for plug and play AI solutions. *IEEE Network*, *35*(1), 372-379

Aggarwal, C. C. (2016). *Recommender systems* (Vol. 1). Cham: Springer International Publishing.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. Industrial Management & Data Systems.

Ben-David, D., & Sade, O. (2018). Robo-Advisor Adoption, Willingness to Pay, and Trust—An Experimental Investigation. Willingness to Pay, and Trust—An Experimental Investigation (December 2018).

Bellamy, R. K., Dey, K., Hind, M., Hoffman, S. C., Houde, S., Kannan, K. & Zhang, Y. (2018). AI Fairness 360: An extensible toolkit for detecting, understanding, and mitigating unwanted algorithmic bias. *arXiv preprint arXiv:1810.01943*.

Bradbury, T. et al. (2014). Robo-advice is coming: What it means, who will buy it-and why. Professional Planner, (69):40.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, *12*(4), 331-370.

Brown, T. et al. (2008). Design thinking. Harvard business review, 86(6):84.

Capponi, A., Olafsson, S., & Zariphopoulou, T. (2019). Personalized robo-advising: enhancing investment through client interactions. Available at SSRN 3453975.

Collins, J. M. (2010). A review of financial advice models and the take-up of financial advice. Center for Financial Security WP, 10(5).

Cheng, X., Guo, F., Chen, J., Li, K., Zhang, Y., & Gao, P. (2019). Exploring the Trust Influencing Mechanism of Robo-Advisor Service: A Mixed Method Approach. Sustainability, 11(18), 4917.

Clavell, G. G., & Peuvrelle, V. (2020). Ethical Issues in Big Data Analytics for Time Critical Mobility Forecasting. In *Big Data Analytics for Time-Critical Mobility Forecasting* (pp. 343-358). Springer, Cham.

Diacon, S. and O'Brien, C. (2002). Persistency in uk long-term insurance: customer satisfaction and service quality. CRIS Discussion Papers, III, University of Nottingham, Nottingham.

Dunbar, I. et al. (2016). Robo-advice-short term fad, or the future of financial advice? Equity, 30(1):8.

Frey, C. B., Osborne, M., et al. (2015). Technology at work: The future of innovation and employment. Citi GPS.

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2021). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *Journal of Service Management*.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. Technological forecasting and social change, 114, 254-280.

Gatzert, N. and Holzmuller (2012). Creating customer value in participating life insurance. Journal of Risk and Insurance, 79(3):645–670.

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital Finance and FinTech: current research and future research directions. Journal of Business Economics, 87(5), 537-580.

Gedikli, F., Jannach, D., & Ge, M. (2014). How should I explain? A comparison of different explanation types for recommender systems. *International Journal of Human-Computer Studies*, *72*(4), 367-382.

Grgurevic, K., & Stroughair, J. (2018). How Gamification Can Attract Consumers to Sign Up. The WealthTech Book: The FinTech Handbook for Investors, Entrepreneurs and Finance Visionaries, 65-67.

Gunning, D., & Aha, D. (2019). DARPA's explainable artificial intelligence (XAI) program. *AI Magazine*, *40*(2), 44-58.

Hagras, H. (2018). Toward human-understandable, explainable AI. *Computer*, *51*(9), 28-36.

Holzinger, A. (2016). Interactive machine learning for health informatics: when do we need the human-in-the-loop?. *Brain Informatics*, *3*(2), 119-131.

Kaiser, T., & Menkhoff, L. (2017). Does financial education impact financial literacy and financial behavior, and if so, when?. The World Bank.

Karimi, A. H., Barthe, G., Schölkopf, B., & Valera, I. (2020). A survey of algorithmic recourse: definitions, formulations, solutions, and prospects. *arXiv preprint arXiv:2010.04050*.

Kimbell, L. et al. (2014). The service innovation handbook: Action-oriented creative thinking toolkit for service organizations. BIS publishers.

Kim, T. W. (2018). Explainable artificial intelligence (XAI), the goodness criteria and the grasp-ability test. *arXiv preprint arXiv:1810.09598*.

Kumar, V. (2009). A process for practicing design innovation. Journal of Business Strategy, 30(2/3):91–100.

Kruse, L., Wunderlich, N., & Beck, R. (2019, January). Artificial intelligence for the financial services industry: What challenges organizations to succeed. In *Proceedings of the 52nd Hawaii International Conference on System Sciences*.

Lin, L.-Y. and Chen, C.-S. (2006). The influence of the country-of-origin image, product knowledge and product involvement on consumer purchase decisions: an empirical study of insurance and catering services in taiwan. Journal of consumer Marketing, 23(5):248 - 265.

Lops, P., De Gemmis, M., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. *Recommender systems handbook*, 73-105.

Malhotra, R. and Malhotra, D. (2006). The impact of internet and e-commerce on the evolving business models in the financial services industry. International Journal of Electronic Business, 4(1):56–82.

Molnár, B., Pisoni, G., & Tarcsi, Á. (2020). Data Lakes for Insurance Industry: Exploring Challenges and Opportunities for Customer Behaviour Analytics, Risk Assessment, and Industry Adoption. In *ICETE (3)* (pp. 127-134).

Ostrowska, M., & Balcerowski, M. (2020). The Idea of Robotic Insurance Mediation in the Light of the European Union Law. In InsurTech: A Legal and Regulatory View (pp. 199-210). Springer, Cham.

Pawelczyk, M., Bielawski, S., Van den Heuvel, J., Richter, T., & Kasneci, G. (2021). CARLA: A Python Library to Benchmark Algorithmic Recourse and Counterfactual Explanation Algorithms.

Pompian, M. M., & Wood, A. S. (2006). Behavioral finance and wealth management: How to build optimal portfolios for private clients.

Pisoni, G., Molnár, B., & Tarcsi, Á. (2021). Data Science for Finance: Best-Suited Methods and Enterprise Architectures. *Applied System Innovation*, *4*(3), 69.

Puschmann, T. (2017). Fintech. Business & Information Systems Engineering, 59(1), 69-76.

Saleiro, P., Kuester, B., Hinkson, L., London, J., Stevens, A., Anisfeld, A. & Ghani, R. (2018). Aequitas: A bias and fairness audit toolkit. *arXiv preprint arXiv:1811.05577*.

Siddiqui, M. H. and Sharma, T. G. (2010). Measuring the customer perceived service quality for life insurance services: An empirical investigation. International Business Research, 3(3):171.

Sokol, K., Santos-Rodriguez, R., & Flach, P. (2019). FAT Forensics: A Python toolbox for algorithmic fairness, accountability and transparency. *arXiv preprint arXiv:1909.05167*.

Sovrano, F., Vitali, F., & Palmirani, M. (2019, November). The Difference between Explainable and Explaining: Requirements and Challenges under the GDPR. In *XAILA@ JURIX*.

Sharma, S., Henderson, J., & Ghosh, J. (2020, February). Certifai: A common framework to provide explanations and analyse the fairness and robustness of black-box models. In *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* (pp. 166-172)

Thiebes, S., Lins, S., & Sunyaev, A. (2020). Trustworthy artificial intelligence. *Electronic Markets*, 1-18.

Van Boeijen, A., Daalhuizen, J., van der Schoor, R., and Zijlstra, J. (2014). Delft design guide: Design strategies and methods.

Van Raaij,W. F. (2016). Understanding consumer financial behavior: Money management in an age of financial illiteracy. Springer.

van Engers, T. M., & de Vries, D. M. (2019, December). Governmental Transparency in the Era of Artificial Intelligence. In *JURIX* (pp. 33-42).

van Thiel, D., Goedee, J., and Reijnders, W. J. M. (2008). Riding the waves. the future of banking starts now.

Verhoef, P. C., Lemon, K. N., Parasuraman, A., Roggeveen, A., Tsiros, M., and Schlesinger, L. A. (2009). Customer experience creation: Determinants, dynamics and management strategies. Journal of retailing, 85(1):31–41.

Vultureanu-Albişi, A., & Bădică, C. (2021, August). Recommender Systems: An Explainable AI Perspective. In *2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)* (pp. 1-6). IEEE.

Xiao, J. J., & O'Neill, B. (2016). Consumer financial education and financial capability. International Journal of Consumer Studies, 40(6), 712-721.

Xue, J., Zhu, E., Liu, Q., Wang, C., & Yin, J. (2018, June). A Joint Approach to Data Clustering and Robo-Advisor. In International Conference on Cloud Computing and Security (pp. 97-109). Springer, Cham.

Zangerle, E., Bauer, C., & Said, A. (2021, September). Perspectives on the Evaluation of Recommender Systems (PERSPECTIVES). In *Fifteenth ACM Conference on Recommender Systems* (pp. 794-795).

Zhang, J., & Liu, P. (2012). Rational herding in microloan markets. Management science, 58(5), pp. 892-912.