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Editorial on the Special Issue on *Insurance: complexity, risks and its connection with social sciences*

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Over the last decade, insurance market has been characterized by significant changes. New regulations, as Solvency II (European Commission 2009) and IFRS17 (European Commission 2021) paved the way to an increasing focus on risk assessment and on market consistent valuation of assets and liabilities. Also the growth of artificial intelligence (AI), used to perform complex computational tasks, is revolutionising financial services, particularly within insurance practices (see EIOPA 2021). Nowadays, data represent a primary strategic asset and a source of competitive advantage in financial firms and the inherent value of predictive analytics in insurance is showing itself in myriad applications (see, e.g., Hyong and Errol 2015; Maynard et al. 2022). Additionally, an emerging wave of insurtech solutions are trying to transform insurance business through the introduction of Big Data, Machine Learning, and AI capabilities (see, e.g., McFall et al. 2020). In the insurance context, several fields have been characterized by the use of Machine Learning and AI methodologies. Predictive analytics tools can collect data from a variety of sources to better understand and predict the behaviour of policyholders. Companies are indeed collecting data from telematics, distribution channel and customers interactions, smart homes and even social media to better understand and manage their relationships, claims, and underwriting and so on.

Along with the increasing complexity of the problems raised by paractitioners as well the huge availability of semistructured data the literature has tried to offer solutions and methodological interpretation of not yet explored phenomena (Richman 2021). Focusing on non-life insurance, complex network and machine learning techniques have been adopted for transforming the claim settlement process and detecting frauds. In particular, sophisticated methods are improving predictive accuracy in identifying the risk of fraud

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and enabling loss control units to achieve higher coverage with low false positive rates (Aslam et al. 2022). A wide literature explores how to improve customized premiums using data collected from black-box technologies. In this context, special attention has been paid to predicting motor insurance claims using telematics data and assessing the relation between driving behaviour and risk (see, e.g., Henckaerts and Antonio 2022; Gao et al. 2019; Gao and Wüthrich 2018, 2019; Guillen et al. 2020; Pesantez-Narvaez et al. 2019; Verbelen et al. 2018). Machine learning techniques made it also feasible to calculate claims reserves on individual claims data (see, for instance, Łukasz et al. 2020; Gabrielli et al. 2020; Wüthrich 2018).

Also, smart contracts and blockchain technology have reached a level of maturity to empower new market entrants, even with limited capital, to develop new insurance products and business models based on a decentralized nature. One example is represented by Peer-to-peer (P2P) insurance, a business model where individuals join together and pool their resources for mutual aid (see, e.g., Clemente and Marano 2020). Together with blockchain technology, P2P allows for creating a business that ensures an automated and trustworthy transaction environment (EIOPA 2019). Finally, other fields regard the use of machine learning for evaluating the insurability of risks (Eling et al. 2021), customer profitability and loyalty (Fang et al. 2016; Riikkinen et al. 2018), the analysis of legal documents (Zappa et al. 2021; Sabban et al. 2022), the use of virtual assistants and office operations, the identification of potential markets.

Similarly, machine learning has been also applied in context of life and health insurance. For instance, several works focused on the use of neural networks for mortality modelling (see, e.g., Hainaut 2018; Schnürch and Korn 2022; Miyata and Matsuyama 2022; Richman and Wüthrich 2021; Perla et al. 2021; Scognamiglio 2022). The application of data science methods have been also applied for lapse prediction. Lapse risk is indeed a key risk driver for life and pensions business with a material impact on the cash flow profile and the profitability. Therefore, self-learning algorithms can replace the time-consuming process of fitting a lapse model that reflects different policy characteristics and provides best estimate lapse rates, as needed for Solvency II valuations (see, e.g., Azzone et al. 2022; Reck et al. 2022). Health care costs have been also modelled via machine learning techniques in order to both contain medical expenditure and improve pricing of Health Insurance Plans (Kshirsagar et al. 2021).

In this wide and somehow heterogeneous field, this special issue deals with methodologies and methods that focus on complexity, risks and its connection with social sciences in the insurance and financial context. Indeed, driving, working, health, life, disability, safety, unexpected climate events are several examples of where insurance can play a significant role in at least monetarily compensating for unforeseen losses and thereby reducing the impact of adverse events on individuals and families. With this aim in mind the papers we have selected offer the opportunity to have a view of how insurance actors may help society to increase the welfare. To help reader to select papers of her/his own specific interest in the next few pages a summary of the contributions is reported.

The author of "*A Rank Graduation Accuracy measure to mitigate Artificial Intelligence risks*" (Raffinetti 2023) focuses on the predictive accuracy of machine learning methodology. It provides methods that are viable for both insurance and financial sector but developing specific case studies mostly related to financial topics.

As stressed above, machine learning methods have been applied to solve several problems in insurance and a great focus has been placed to their accuracy in prediction. Indeed, besides the interpretability requirement, one of the most important challenges for machine learning methods is the evaluation of how much are they reliable in unforseen contexts (see, e.g., Kang et al. 2021; Petropoulos et al. 2022). To this end, Raffinetti (2023) provides a new toolkit by extending the existing literature and proposing a Rank Graduation Accuracy measure to mitigate Artificial Intelligence risks. The main idea is to provide a measure based on the evaluation of the concordance between the ranks of the predicted values and the ranks of the actual values. Since the proposed measure is based on the ranks, it generalizes the predictive accuracy problem to all ordered variable scales and allows to gain robustness. The paper also provides an application of the measure to a crypto-asset dataset showing the consistency in the model choice and assuring a greater robustness with respect to classical prediction accuracy measures.

Two papers in the special issue deal with health insurance from a different perspective. The author of "*Financial resilience of insurance network during covid-19 pandemic*" (Cornaro 2022) focuses instead on the financial resilience of the insurance market during the COVID-19 period. The proposed approach exploits network theory to analyze how the insurance market reacted during COVID-19 pandemic. Although the resilience of financial networks has been widely studied in the literature (see, e.g., Amini et al. 2013; Clemente and Cornaro 2022; Cerqueti et al. 2019; Kou et al. 2022; Leduc and Thurner 2017), very few attempts have been done with regard to the insurance market. In particular, on the one hand, the methodology in Cornaro (2022) allows to assess the financial resilience of the insurance market in period of crisis and to identify systemic insurers. On the other hand, this work provides novel local and global measures of resilience based on the quantification of the reactions of firms to a shock propagation in the network. The case study, based on a very large set of insurers and for a significant time period, confirms how the global resilience indicator evolves consistently with the main crisis events observed in the market and detects the first wave of COVID-19 as a unusual perturbation in the network.

Also the authors of "*A quantitative analysis on the effect of COVID-19 in a private health insurance plan expenditure*" (Biancalana and Baione 2022) focus on the effect of COVID-19 on the insurance market. Specifically, they consider a private Health Insurance Plan in order to investigate if the policyholders' behaviour in a post-pandemic context has been affected by the COVID-19 effects. To this end, the authors exploit a Tweedie Generalized Linear Model using empirical data from a private insurance plan operating in Italy to forecast the health care expenditure in the pandemic and post-pandemic period. Results emphasize the expected reduction of the number of claims in the pandemic period due to the containment measures adopted by the Italian government (as lockdown measures). Additionally, the models also confirm that the post-pandemic situation is returned to a state of normality in terms of policyholders' behaviour.

The authors of "*Multi-country clustering based forecasting of healthy life expectancy*"

Levantesi et al. (2023) deal instead with Healthy Life Expectancy (HLE), a widely used indicator that measures the number of years individuals at a given age are expected to live free of disease or disability. HLE is indeed a composite measures of health that combine mortality and morbidity data to represent overall population health on a single indicator (see, e.g., Sullivan 1971). It has particular relevance for planning the provision of health care to elderly populations and appropriately pricing Long Term Care insurance products. The authors propose a methodology that simultaneously forecasts HLE for groups of countries based on similarities in their HLE patterns. The proposed approach combines functional data clustering and a multivariate random walk with drift for identyfying clusters of countries and for forecasting simultaneously the HLE indices for the populations in the same cluster. In this way, both the overall trends of the evolution of life expectancy on a global level and the country-specific patterns are taken into account. The authors also develop a numerical application based on the data of the HLE indices of 31 countries in the world for the period 1990–2019. Three alternative clusters have been identified that allow to emphasize similarities and differences between the selected countries.

Finally, factor importance analysis is applied in "*How do demand-side incentives relate to insurance transitioning behavior of publichealth insurance enrollees? A novel voting ensemble approach for ranking factors ofmixed data types?*" (Zhang et al. 2023) to study the insurance transitioning behaviour of the public health insurance enrollees in the United States. Through two novel ranking scores, the proposal allows to assess variable importance using a dataset that combines both numerical and categorical covariates. An analysis based on Medical Expenditure Panel Survey data has been developed showing that the proposed approach proves to be competitive with respect to the existing literature.

In conclusion, the special issue on " *Insurance: Complexity, Risks, and its Connection with Social Sciences*" sheds light on the multifaceted nature of insurance and the profound influence social sciences have on shaping its landscape. This collection of articles underscores the intricate interplay between insurance practices, risk assessment, and societal dynamics. The diverse perspectives presented offer valuable insights into improving insurance methods, enhancing risk management strategies, and promoting greater inclusivity and fairness. We do thank the Authors that contributed to this special issue for having promoted to a deeper understanding of the complex relationship between insurance and social sciences. Moreover, this special issue serves as a call to action for researchers, practitioners, and policymakers to embrace interdisciplinary collaborations and leverage social science knowledge to drive innovation and positive change in the insurance sector. By harnessing the power of social sciences, we can foster a more resilient and responsive insurance industry that better serves the needs of individuals, communities, and societies at large.

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