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Developing Ethical Usage Guid-elines for Customers of Artificial Intelligence and Big Data Analytics: Ethical Applications within Realm of Big Data Analytics

Mahdi Fadil Khaleel[1*], Zainab Mohammed Abdulkareem[2], Yaser Issam Hamodi[3]

[1]Technical Institute - Kirkuk, Northern Technical University, Iraq.*
[2]Kirkuk Technical College Engineering, Northern Technical University, Iraq.
[3]Minister Office, Ministry of Higher Education & Scientific Research, Iraq.

Corresponding Email: [1]mahdi.fadil@ntu.edu.iq*

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***Abstract:** In both the operational and customer-facing facets of the insurance sector, big data analytics and ever-evolving machine learning and artificial intelligence (AI) capabilities have become indispensable. Insurance-related goods and services, which cover things like business property insurance, auto insurance, and personal health insurance, are essential for advancing the economy and society. The significance of artificial intelligence and machine learning in preserving this equilibrium within the insurance industry has already been established. However, as AI and machine learning are used more frequently, it creates new issues and calls into question the industry's moral standards. In order to shed light on any potential new conflicts and concerns, it is vital to look into the ethical ramifications and conundrums surrounding the use of data in insurance innovation. In order to examine and gain a deeper understanding of the ethical landscape relating to the tensions surrounding the use of big data analytics, AI, and machine learning methodologies to sustain the operations of the insurance industry, this study combines the insights of insurance professionals with the expertise of an AI ethics specialist.*

***Keywords:** Big Data, Artificial Intelligence, Machine Learning.*

1. INTRODUCTION

As the importance of ethical considerations in technology grows, a novel idea in big data analysis is the integration of ethical principles and guidelines into every stage of data collection, processing, and analysis[1]. This approach aims to ensure that data-driven decisions are not only accurate and efficient but also morally sound, fostering trust and transparency in the use of vast datasets for societal benefit [2].

One of the most notable and notable effects of the technological revolution that ushered in the digital age is artificial intelligence. Its intelligent uses have had a significant impact on many facets of life and helped to serve and advance humanity. The area of intelligent machine engineering, which strives to develop hardware and software capable of thinking like the human brain, provides the foundation for artificial intelligence. Using this strategy, artificial intelligence was able to produce an electronic version that was comparable to a human and had the capacity to learn, analyze facts and information, and infer links. Therefore, he can make appropriate decisions to respond to the situations faced by the electronic machine, and exploit those decisions to carry out the tasks assigned to it.

In an era where big data has become the cornerstone of decision-making and innovation, the need for ethical considerations in data analysis has never been more critical. The integration of Ethical AI principles into big data analysis practices marks a significant step forward in ensuring that data-driven decisions not only benefit organizations but also uphold societal values and ethical standards[3].

Additionally, there are more general worries in the research field related to the commercial applications of user data as well as the conflicts with privacy issues, profiling, and user perception. The potential for opacity in these novel risk assessment methodologies and the necessity of aiming for clearness have also been the subject of lengthy arguments. These discussions represent only a fraction of the broader discourse on disruption, insurance solidarity, and evolving societal perspectives and apprehensions [4].

Algorithmic bias is inherently intertwined with data quality, as the fine-tuning of AI algorithms is fundamentally shaped by the data sets employed during its development. Whenever the training data set exhibits biases toward protected qualities or flaws in other dimensions, these biases become ingrained at the heart of the evolving Big Data Analytic (BDA’s) and AI systems, ultimately result in unjust discriminations. The insurance context, it's not just about the volumes of the data, the notions of granularity and interconnectedness of paramount significance. Granularity pertains to the exceptional level of precision at which an individual's characteristics and behaviors can be recorded [5].

It is crucial to consider the specific goal or commercial environment for which an AI system is designed when evaluating AI ethics in the insurance arena. Whether it is meant for pricing, streamlining business operations, or conducting market analysis, this context not only shapes the environment but also provides insights into the probability and potential extent of harm that might occur. Therefore, a thorough examination of AI ethics requires the adoption of a comprehensive viewpoint that encompasses the fundamental AI technology embedded in the an algorithms, the datasets that are used in the application's design & continuous improvement, and the broader business and societal contexts in which the technologies operates[6].

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A significant sector within the insurance industry in which ethical and governmental values like fairness, anti-discriminations, & minimizing harm intersect is motor insurances. The potential for conflicts between the principles of fairness and discrimination. came to the forefront in the Test-Achat case, a 2011 landmark that reached the European Court of Justice. This case established that it is not acceptable for insurance practices to providers the base pricing decisions on gender grounds[7].

For example In their work, Richardson, Petter, and Carter (2021) present a significant challenge to the information systems (IS) community. They highlight the multitude of ethical considerations that arise when employing big data analytics (BDA). As scholars within the IS field, it is imperative for us to engage in a thorough and sustained conversation regarding our responsibilities as researchers, educators, and professionals in promoting the responsible use of data and analytics by organizations and individuals. On this particular issue, I wholeheartedly concur with their perspective[8].

Customization of Ethical Guidance is Essential:

The ethical challenges encountered by stakeholders in these scenarios exhibit a broad spectrum. The available ethical responses, in turn, vary according to the individuals' organizational roles and hierarchical levels[9]. As Information Systems (IS) researchers, educators, and practitioners, we find ourselves at the intersection of these diverse stakeholders and their respective use cases, among many others. To offer meaningful ethical guidance to these stakeholders, we must possess a well-founded knowledge base, cultivated through diligent scholarly work, that delves into the specific ethical quandaries recurrently confronted by those we advise. Currently, such a comprehensive knowledge base is lacking[10].

Additionally, we must acknowledge that there is no one-size-fits-all set of values or principles, such as PAPAS or FAccT, that will universally apply. Values are subject to conflicts—both between organizations and within them[11]. For example, a data-selling company that contracts data "as is" (and is thus immune to legal repercussions for data inaccuracies) has a different interest in upholding the accuracy principle compared to a company making multimillion-dollar decisions based on that data. Conflicts in values can also emerge within organizations; for instance, the data stewards responsible for enforcing privacy regulations may hold differing perspectives on privacy compared to company data scientists eager to extract insights from data. Furthermore, individuals and roles themselves may grapple with value conflicts; data providers, for example, may face a dilemma between preserving privacy through anonymization or aggregation of data on one hand and ensuring accuracy and usefulness by providing data at a granular level on the other[12].

The Importance of Ethical AI:

As we navigate through the vast seas of data generated daily, ethical concerns surrounding data collection, processing, and analysis have gained prominence. Issues related to privacy, bias, fairness, transparency, and accountability have sparked discussions[13].

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Artificial Intelligence (AI) has transformed numerous aspects of our lives, revolutionizing industries, automating tasks, and providing unprecedented insights from vast amounts of data. However, with this technological advancement comes a significant responsibility to ensure that AI is developed and used ethically[14].

Big data analysis has unrivaled power in today's data-driven surroundings. It has revolutionized industries, informed decision-making, and opened up new frontiers for innovation. However, the massive amounts of data available present a double-edged sword, as they also raise significant ethical concerns[15]. As data analytics become increasingly integrated into our lives, addressing these ethical challenges is imperative.

The trend towards more applications of artificial intelligence is necessary to provide humanity with prosperity and increase its well-being, but the fear of its negatives and threats remains, and here there appears to be an urgent need to search for a regulatory and ethical mechanism that governs the work of artificial intelligence so that it achieves a balance between continuing its development and taking care to avoid its negatives. This requires the need to search for educational and legal ways to develop an ethical value system that governs the relationship between humans and machines and between human individuals who deal with artificial intelligence, which may contribute to achieving benefit from artificial intelligence applications without compromising basic human rights[16].

To talk about an ethical framework for dealing with the artificial intelligence community, we must begin by acknowledging that ethics in the artificial intelligence community is the art of living life and finding the best alternative in light of the set of available alternatives that surround humans, and this ethics must not be based on the principle of coercion or obligation to laws, but rather must To be based on the fact that the human conscience is the first moral authority in this society, meaning that the source of moral obligation in the artificial intelligence society is the human being himself and from within him, so that this ethics focuses on the principle of commitment, not obligation. The ethics of the artificial intelligence society differ from the ethics of the era of the industrial revolution. In which ethics were formulated in the form of laws and legislation. Perhaps this is due to the ethics of the artificial intelligence community being characterized by abolishing police control and transforming it into self-censorship, with the psychological reference replacing the social reference[17].

The ethical framework that should prevail in the artificial intelligence community must be characterized as a moral authority that governs the behavior of all people, provided that the principles and values of this ethical framework are compatible with the ideas of freedom and responsibility. The ethical framework is greater and stronger than the legal or legal framework. The artificial intelligence community's justice does not It can be accomplished by law alone, but it is also accomplished through virtues, values, and ethics that go beyond individual interests and stem from religious teachings and generally accepted social values [18].

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Ethic and Big Data

In the present day, our approach to conducting activities must skillfully harmonize the realms of risk and innovation. Big Data's enormous effects, which seamlessly integrate company operations with personal lives, have become a potent catalyst for moral dilemmas including core ideas like identity, confidentiality, ownership, and reputation [19].

As we develop products and services that make use of Big Data technology, it is crucial that we articulately explain and align our values with our actions. Only then will we be able to successfully tackle these issues. Using a structured framework gives people a shared language and encourages open communication, which improves our understanding and application of these ideals.

This content delves into the convergence of ethics and Big Data, providing insights into its scope and boundaries. It explicitly outlines strategies for engaging in discussions and nurturing dialogues on this abstract subject, which carries concrete, real-world consequences[20].

We will introduce an all-encompassing framework for discussing ethics within the realm of Big Data. Key components of this framework include: relevance to your data handling procedures, the profound impact of big data on principles like identity, privacy, ownership, and reputation, the identification of ethical decision points, and the usage of value personas as a discussion starter and tool to encourage agreement between values and behavior are just a few of the things that should be considered. The benefits of big data innovation and any potential issues should be properly balanced [21].

An accomplished professional with a nearly two-decade-long career, Kord Davis was a former Principal Consultant at Cap Gemini. He has provided technical consulting, corporate strategy, and analysis support to more than 100 firms of various sizes and focuses. Among these are well-known clients including Western Digital, Autotask, Microsoft, Intel, Sisters of Mercy Healthcare, Nike, Bonneville Power Administration (BPA), Northwest Energy Alliance (NEEA), Bill & Melinda Gates Foundation, Fluke, Merix, Roadway Express, and Gardenburger. Kord brings an insatiable curiosity, analytical precision, and a passion for leveraging technology to increase our efficiency in attaining goals[22] by combining his academic training in philosophy with his work experience in telecommunications. He graduated from Reed College with a BA in Philosophy and holds credentials in business transformation, systems modeling, and communication. He has also received formal training as a workgroup facilitator. Figure 1 shows the four components of big data.

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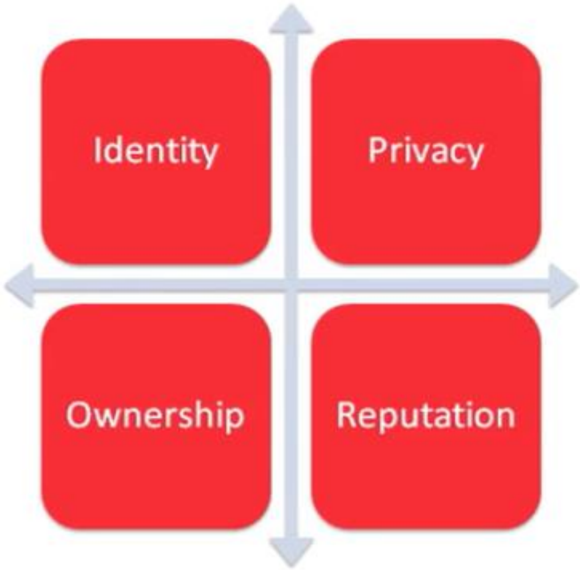

Figure 2: the four aspects of Big Data.

The body of literature that amalgamates big data and ethics is expanding rapidly. From 2001 to 2016, there has been a marked escalation in the utilization of big data, alongside an increase in both real and perceived ethical transgressions. Key sectors significantly impacted by ethical concerns related to data encompass healthcare, education, and information technology. Within these sectors, an examination of the reviewed articles reveals the presence of four primary themes (refer to Table 1). These topics include ownership, security, privacy, and decision-making. According to Zwitter (2014), the industry is moving toward a viewpoint in which ethics should no longer be seen as individual decisions leading to specific and informed outcomes, but rather as actions taken by many people who are frequently unaware that their actions may have unintended consequences for others. Each of these four themes is thoroughly explained in the sections that follow. [23].

Table 1. Prominent the Ethical Themes Explored in this Literature

Theme	**The Ethical Challenge**	**Example**
The Privacy	Unauthorized Sharing of Personal Data – Deidentification of Data	Detecting the Ebola Outbreak in 2020 through Data Analysis A 2022 Facebook Study Investigating User Emotions Without Their Informed Consent
The Security	Securing Data Against External Threats	Security Weakness Results in Ransom of Hospital Data in 2023

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The Ownership	The Legitimate Ownership of Data Employed for Analytics	Studying Illicit Activities Where Courts Seek Data for Constructing a Legal Case Against an Individual
The Evidence Based Decision Making	Utilizing Data Exclusively for Population-Based Quantitative Decision-Making	States Determine Welfare Criteria Solely Based on Income

Data Analytics and the Influence of Ethics on the Conceptual Framework

The conceptual framework for big data analytics processes, concerning the handling of big data, comprises two primary concepts, each with its own subsets: Big Data and Analytics (which include analysis/review and justification) are two terms that refer to the collection, storage, editing, and representation of large amounts of data. When dealing with sensitive data sets, data management is crucial in this framework. Ethics concerns permeate every facet of this conceptual framework, with major focal points identified in the literature being privacy, security, ownership, and evidence-based issues. Data analysts must exercise caution when working with big data, as it is erroneous to assume that big data is inherently devoid of controversy. An underlying assumption is that analysts will consistently make ethical decisions in their handling of big data. Please refer to Table 2 for a detailed breakdown of the conceptual framework, the associated questions reflecting concerns, and the prevalent ethical themes[25].

Table 2. Big Data Analytic Procedures: Conceptual Frameworks, Inquiry Points, & Ethical Dilemmas

Big Data	**The Concern**	**Ethical Themes**
Acquisition and Storage of Extensive Data	Is the use suitable? Is the source suitable? Who own the data – are they have access after collection?	The Privacy The Security The Ownership Evidence-Based on Decision Making
The Mining	Is the source respected?	
The representation of the BD	Does the data genuinely reflect the population or individuals accurately?	
The analytics	**Concerns**	**The Ethical Themes**
The Analysis &Review	Are the mistakes made? who is responsible??	Evidence-Based Decision Making Ownership
Explanations	Has the data undergone substantial alterations? What are the implications of disclosing the results?	

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An Ethical Model with a Hierarchical Framework for Big Data and AI Systems in the Insurance Sector

Understanding AI-driven insurance systems presents a number of intrinsic difficulties, including a lack of clarity around the meaning of the phrases "AI" and "big data" in the context of insurance. Frequently, the AI system is viewed as a distinct technical entity, and even as a mysterious "black box" clarity and expression are severely hampered by this intricacy. Nevertheless, it is feasible to outline this evolving technology in abstract terms, rendering it more amenable to ethical examination and discussion. To a certain extent, this paper is motivated by the aspiration to establish a more precise foundation for ethically overseeing and regulating AI and big data analysis in the insurance sector.

In our proposed framework, we outline four hierarchical levels that define the context, which can be categorized into four distinct tiers. First, we have the product-market level, particularly significant within the insurance industry. Second, the InsurTech level, intricately connected with insurance company operations. Third, we consider the AI capabilities level, which emulates human thinking and forms the basis for InsurTech. Lastly, we delve into the innermost workings of the AI system itself. This ultimate tier necessitates a comprehensive analysis of how algorithms function, their training with extensive datasets, and the exploration of crucial issues such as algorithmic bias. You can visually grasp this hierarchical model of AI in insurance in the Figure 1.

This model's structure draws upon the principles of systems theory, wherein a high-level insurances products can be envisioned as a composite of sub-system, further divisible into more detailed components. This concept aligns with the engineering discipline's perspective on complex systems, which encompass both the organizational & technical systems within a multi-level structure. In this paper, we conceive of insurance as a very complex system which that incorporates intricate relationships spanning technicals and socials system. This systems-oriented view resonates with florid i's perspective on levels of abstraction. The notion of employing layers and levels to expound various ethical aspects of technologically application and use cases has gained prominence, especially in socio-technological and ethical analyses, partly influenced by florid but also reflecting a broader methodologically discourse.

The central justification for embracing this approach lies in the necessity to gain a profound understanding of insurance and the ethical implications entailed. To achieve this, it is imperative that we provide clear and explicit definitions for insurance products and services. This includes a detailed delineation of the specific roles fulfilled by digital and AI technologies, as well as the application of Big Data Analytics (BDA). Mere scrutiny of ethical concerns within the broader framework of insurance product marketing (at level 4) proves insufficient. Rather, we must embark on an exploration of the underlying sub-systems and layers that operate beneath the surface of insurance products. This exploration is indispensable for comprehending the intricate mechanisms governing the interplay between technical and social systems in the creation of an insurance service.

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The model is organized into four distinct tiers: (1) (AI) technological, (2) AI capability, (3) insurances technology, and (4) insurances product and services. This conceptual framework offers two viable implementation approaches: the top-down approach, commencing with insurance services, or the bottom-up approach, initiating with AI technology.

According to the bottom-up methodology, AI technology, which is defined in terms of algorithms and data, is the fundamental component of modern insurance services, dictating the goals and architecture of the system. The necessary digital tools are included in this tier, together with the necessary digital technology, data sources, initial AI design, algorithm training procedures, and core AI technology to smoothly integrate the core AI technology into a larger digital and business context.

At its essence, AI technologies empower the acquisition of skills, as depicted in the model's second tier. These AI skills are characterized by human behavioral traits, serving as the fundamental building blocks for insurance-specific technology at the third level. In this context, insurance technology encompasses a wide range of distinct insurance processes. These processes span from the intelligent management of policy records and the creation of risk assessment models to modular insurance services, such as robo-advisory services, accident prevention, and e-services for policy adjustments.

Certainly, as an example, electronic services enhance the way customers engage with their insurance provider, allowing policyholders to foster enduring connections by effortlessly adjusting policies, renewing services, and filing claims. Pricing in the insurance industry is a crucial operation that is recognized as a separate business process and supported by level 2 AI capabilities and level 1 foundational AI technologies.
With the use of a combination of insurance technologies, Level 4 consists of insurance products and services that produce recognizable insurance goods like health, home, and auto insurance. Figure 2 illustrates the hierarchical AI insurance model that has been presented.

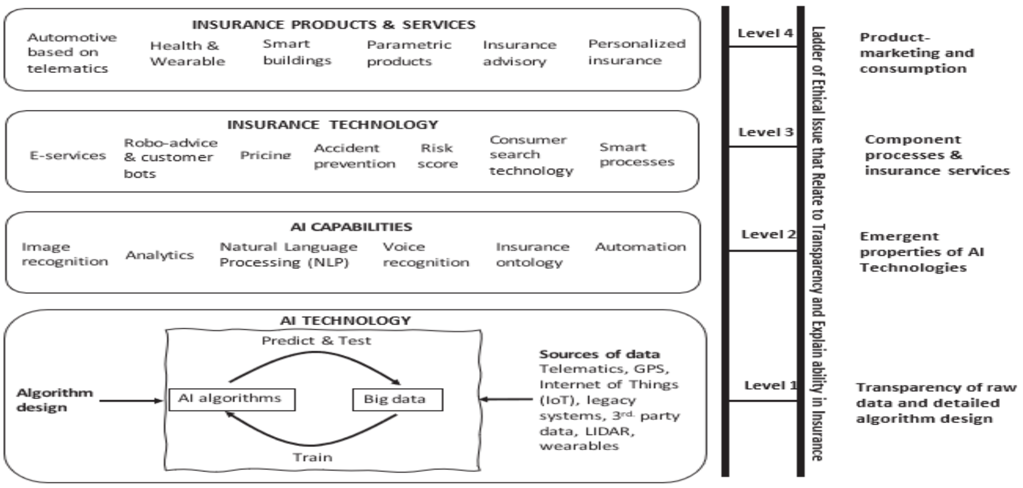

Figure 2. Hierarchical of ethics model AI & big data in insurance.

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Approaches to Methodology and Ethical Evaluations

Suggesting that the intricacies of human interactions and the intricacy of the social milieu can be simplified into a self-contained network of nodes and edges disregards crucial insights derived from a wide range of disciplines, including machine learning, sociology, and economics. It's essential to recognize that datasets are not, and can never be, impartial and devoid of theoretical underpinnings, merely awaiting researchers to unveil their secrets. They necessitate active interpretation by researchers, each of whom brings their own unique perspectives. Nobody reads from an impartial or conclusive position, as historian James Clifford so eloquently put it. This crucial warning is frequently overlooked in new accounts that make the claim to correct the record or fill in knowledge gaps on "our" part (Clifford & Marcus, 1986, p. 18) [26].

Within this compilation, three articles directly tackle methodological challenges related to sampling and bias, with a particular focus on the intricate task of achieving representativeness when working with social media data. Lawrence Busch scrutinizes the vulnerabilities of big data analyses, highlighting issues like distortion, errors, bias, and misinterpretation. He emphasizes the criticality of data construction methods, especially since these datasets play a pivotal role in shaping policy decisions. Busch underscores the intricate trade-offs involved in balancing data set size and apparent precision.

Kevin Driscoll and Shawn Walker provide a clear demonstration that even when employing thorough and robust methods for collecting social data, research outcomes can still exhibit biases. Their work emphasizes the importance of understanding how data access and technological infrastructure can impact the results of experiments. Furthermore, they show how even in universities with ample funding and "full" access to Twitter's database, little changes in timing or network connectivity can have a big impact on the results of a single experiment. Driscoll and Walker warn against drawing conclusions from such studies that can be applied to larger-scale occurrences, especially in light of Twitter's relatively small user base.

Jim Thatcher grapples with the inherent challenges of representation within the "data fumes" generated by geolocation-based apps. He notes that platforms like Foursquare are predominantly used by a small, urban, and relatively privileged segment of the population. Even in this narrow environment, the characteristics of the applications themselves—which are frequently created by a very small, homogenous set of developers—have an impact on the data that may be collected. Thatcher cautions scientists working with these kinds of data that "the boundaries of knowledge are defined by the data infrastructure of private corporations".

The data sets from social media platforms are by their very nature exclusionary because of the populations they represent and the methods used to get them, as all of these articles make clear. The authors urge us to take into account the ethical implications of using such data sets, especially when they are used to influence decisions that affect entire populations, whether in policymaking, planning, or resource allocation [27].

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2. REFERENCES

1. EIOPA (2021). Artificial Intelligence Governance Principles: Towards Ethical and Trustworthy Artificial Intelligence in the European Insurance Sector (European Insurance and Occupational Pensions Authority).
2. EIOPA (2019). Big Data Analytics in Motor and Health Insurance: A Thematic Review (European Insurance and Occupational Pensions Authority).
3. Agrawal, A., Gans, J.S., and Goldfarb, A. (2019). Artificial intelligence: the ambiguous labor market impact of automating prediction. J. Econ. Perspect. 33, 31–50.
4. Jang, J.A., Kim, H.S., and Cho, H.B. (2011). Smart roadside system for driver assistance and safety warnings: framework and applications. Sensors 11, 7420–7436.
5. Masters, J. (2012). Telematics Making Fresh Gains, 18 (ITS International).
6. Shannon, D., Jannusch, T., David-Spickermann, F., Mullins, M., Cunneen, M., and Murphy, F. (2021). Connected and autonomous vehicle injury loss events: potential risk and actuarial considerations for primary insurers. Risk Manag. Insur. Rev. 24, 5–35.
7. Titsworth, T. (2002). Telematics might steer your car into the future. IEEE Multimedia 9, 9–11.
8. Cie´slik, B. (2017). Telematics in automobile insurance. Collegium Econ. Anal. Ann. 45, 79–92.
9. Constantinescu, C.C., Stancu, I., and Panait, I. (2018). Impact study of telematics auto insurance. Rev. Financ. Stud. 3, 17–35.
10. Handel, P., Skog, I., Wahlstrom, J., Bonawiede, F., Welch, R., Ohlsson, J., et al. (2014). Insurance telematics: opportunities and challenges with the smartphone solution. IEEE Intell. Transp. Syst. Mag. 6, 57–70.
11. Husnjak, S., Perakovic´, D., Forenbacher, I., and Mumdziev, M. (2015). Telematics system in usage based motor insurance. Proced. Eng. 100, 816–825.
12. Yoon, D., Choi, J., Kim, H., and Kim, J. (2008). Future automotive insur- ance system based on telematics technology. In 2008 10th International Conference on Advanced Communication Technology (IEEE).
13. Cunneen, M., and Mullins, M. (2019). Framing risk, the new phenomenon of data surveillance and data monetisation; from an 'always-on' culture to 'always-on' artificial intelligence assistants (Hybrid Worlds), p. 65.
14. Cunneen, M., Mullins, M., and Murphy, F. (2019). Artificial intelligence as- sistants and risk: framing a connectivity risk narrative. AI Soc. 35, 625–634.
15. Cunneen, M., Mullins, M., Murphy, F., Shannon, D., Furxhi, I., and Ryan,
16. C. (2020). Autonomous vehicles and avoiding the trolley (dilemma): vehicle perception, classification, and the challenges of framing decision ethics. Cybernetics Syst. 51, 59–80.
17. van den Boom, F. (2021). Regulating Telematics Insurance. Insurance Distribution Directive (Cham: Springer), pp. 293–325.
18. Irode, P.L. (2017). An Auto Telematics System for Insurance Premium Rating & Pricing (University of Nairobi).
19. Sreethamol, P., Sulfiya, K., and Vineeth, K. (2018). Consumers percep- tion towards telematics in insurance. Res. J. Human. Soc. Sci. 9, 657–662.

20. Kuo, K., and Lupton, D. (2020). Towards explainability of machine learning models in insurance pricing. arXiv arXiv:200310674.
21. Ma, Y.-L., Zhu, X., Hu, X., and Chiu, Y.-C. (2018). The use of context-sen- sitive insurance telematics data in auto insurance rate making. Transportation Res. A: Policy Pract. 113, 243–258.
22. Hollis, A., and Strauss, J. (2007). Privacy, Driving Data and Automobile Insurance: An Economic Analysis (University Library of Munich: Germany.: MPRA Paper 11091).
23. Filipova-Neumann, L., and Welzel, P. (2010). Reducing asymmetric infor- mation in insurance markets: cars with black boxes. Telematics Inform. 27, 394–403.
24. Kargupta, H. (2012). Connected cars: how distributed data mining is changing the next generation of vehicle telematics products. In International Conference on Sensor Systems and Software, F. Martins and H. Paulino, eds. (Berlin, Heidelberg: Springer).
25. Cunneen, M., Mullins, M., Murphy, F., and Gaines, S. (2019). Artificial driving intelligence and moral agency: examining the decision ontology of unavoidable road traffic accidents through the prism of the trolley dilemma. Appl. Artif. Intell. 33, 267–293.
26. Vallor, S. (2016). Technology and the Virtues: A Philosophical Guide to a Future Worth Wanting (Oxford University Press).
27. Mizgier, K.J., Kocsis, O., and Wagner, S.M. (2018). Zurich Insurance uses data analytics to leverage the BI insurance proposition. Interfaces 48, 94–107.