HUK-COBURG: The Implementation of an AI-Enabled Behavioural Insurance Business Model using Geo-Spatial Data

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Abstract

Automotive insurance is undergoing digital transformation that exploits new forms of big data and Artificial Intelligence (AI) systems. Geo-spatial data from GPS and telematics systems enables innovative risk modelling to evaluate driver behaviour and leads to the creation of new insurance services and novel insurance business models. A research framework is proposed to analyse AI-enabled business models and applied to a detailed case analysis of behavioural insurance in HUK-COBURG. The results illustrate the application of geo-spatial data in an insurance context and demonstrate the utility of the research framework to analyse new AI-enabled business models. The analysis identifies important implementation issues and shows that the strategic logic, regulatory and ethical context are important elements of business models. The empirical analysis reveals the strategic properties and effects of the data flywheel concept, which has general applicability. The theory framework and empirical results have important implications for other markets and theoretical contexts.

Keywords: Geo-Spatial data, behavioural insurance, business model theory, implementation

1. Introduction and Motivation of the Paper

The digital transformation of organisations and markets has become pervasive, with change occurring in all types of organisations, across market sectors, and on a global scale [1][2] and there is a new wave of AI and Insurance Technology (InsurTech) applications that creates new organisational and strategic capabilities in insurance firms [3][4]. Digital technology is used to improve the performance of incumbent firms and facilitates new start-ups to enter existing markets with radically different value propositions [5], fresh approaches to business problems and innovative business models [6][7]. The insurance sector has lagged advanced markets in terms of digital disruption, but this is now changing with very high levels of investment into InsurTech [8] and widespread evidence of substantial change and transformation of incumbent firms, product innovation and the adoption of Artificial Intelligence (AI) [9].

Insurance markets are an interesting sector to analyse because insurance is a fundamentally important service to society in areas as diverse as property, casualty, life insurance, health and automotive. The strategic potential of Insurance Technology (InsurTech) is demonstrated by the high level and recent growth in spending and investments in this area [10]. Regulatory bodies also recognise the crucial role of insurance in society, with strict rules and governance on firm behaviour and governance, including the new and emerging issues associated with Artificial Intelligence (AI) and ethics in insurance [11][12], in particular, transparency and explainability of algorithms, fairness and non-discrimination, and the associated use of big data, especially personal demographic and behavioural data [13]–[15].

Insurance is fundamentally an information and risk business, and it is therefore natural that digital technology is at the core of new products, redesign of business processes, changes to insurance business models and more broadly, innovation in products, customer interactions, value creation and the insurance value chain [16][17]. Digital technology has already had a profound impact on insurance markets, e.g., the widespread use of price comparison websites for automotive and home insurance, improvements to insurance business processes from Robotic Process Automation (RPA) technology, automated e-service, sophisticated claims management systems and advanced, industry-wide fraud detection. However, these applications represent the start of a digital transformation, not the end point. In the automotive insurance market, the advent of big data, in particular the emergence of telematics technology that can capture detailed and accurate driving behaviour based on GPS sensors, mobile phone technology and in-car systems, creates a market discontinuity where existing and historical approaches have much less relevance than insights and evidence from experimentation and cutting-edge business practice.

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A significant number of business and consultancy articles focus on the role of new entrants in insurance [18][12], the disruptors, and tend to neglect the innovation from existing firms. In this paper, a detailed case analysis of the leading German home and automotive insurance company, HUK-COBURG, is presented. The focus is on analysing the design and implementation of a new business model that is based on behavioural insurance, and which uses geo-spatial, telematics, AI and advanced analytics.

2. Research Questions and Framework

Two research questions are posed to develop a research framework, inform the literature review and to structure the analysis of the case data. The principal research question is: *How can Artificial Intelligence (AI) systems, new forms of geo-spatial data, and related digital and analytics technologies be deployed to design a behavioural insurance business model?* The secondary question concerns the implementation challenges of a behavioural insurance business model in a regulated and mature market.

2.1 Research Framework: Behavioural Insurance Business Model and Implementation

Geo-spatial data provides a rich set of opportunities for risk assessment and mitigation in automotive insurance that differ from the traditional methods of inferred risk from historical data patterns using statistical methods and risk pooling. This new method of risk assessment also raises new possibilities in areas such as risk mitigation, new forms of customer communication and rich insights into customer behaviour and accidents, and the associated outcomes in terms of human and economic costs. It also fundamentally changes the design and flow of information and business processes to manage the rich, complex and diverse behavioural data.

The design of a behavioural insurance business model is a difficult problem because it represents a significant departure from traditional insurance services. The key difference is the estimation and evaluation of risk. It is also necessary to consider other important elements in the business model to understand how geo-spatial technology operates within the broader context of business and competition, regulated markets, and the need for ethical factors to be considered in the use of very detailed, personal customer data.

The proposed research framework is a synthesis of previous research and emerging ideas and concepts from the insurance, AI and big data research literature. It also reflects the practice of a leading insurance company that is involved in implementing a behavioural insurance product in the German automotive market. The framework is composed of five elements:

i. Technical and big data analytics [19], [20]
ii. Business processes and information flows [21]
iii. Strategic logic [22], [23]
iv. Ethical framework[24], [25]
v. Regulatory context[11]

Technical and big data analytics refers to the technical challenges related to the deployment of GPS, telematics and data analytics to interpret complex behavioural driving data in an insurance context.

Business processes and information flows refers to the core information exchanges between customers and the insurance firm, and the associated business process and organisational changes inherent in the design of a new business model. Taken together, these first two elements describe the operational aspects of the business model and a powerful method to describe these variables in a cohesive manner is to use a Data Flow Diagram (DFD). Data flow diagrams are an elegant way of describing and illustrating how the technical, data, and organisational processes relate to each other to create an overall logical outcome, in this case, a behavioural insurance service.

The *strategic logic* is concerned with the competitive performance of the business model, e.g., profitability, market share, position in the customer lifecycle, growth, customer acquisition and retention. The *regulatory context* is primarily concerned with GDPR requirements for handling complex and detailed personal customer data. The *ethical* framework is now an integral component of the regulatory and market environment and include difficult issues such as transparency and explainability of complex algorithms, bias, and fairness [26].

Each of these elements of a business model is important individually and together they give a comprehensive overview of the operations and logic of the business model within a strategic, regulatory and ethical context. The implementation challenges relate to problems and opportunities associated with applying the ideas and concepts in practice. This research framework enables the analysis of individual implementation challenges, e.g., to the strategic logic, or a technical design aspect of the business model, and by taking a synthesis of these variables, can provide important insights into the overall challenge of transitioning from a traditional insurance service to a business model based on behavioural insurance concepts.

3. Case Study Method

InsurTech is placed within an organisational setting and context to understand the nature of the implementation process and the role of behavioural insurance in changing the business model of the firm and to understand how the different elements of the strategy fit together to form a coherent narrative, with accurate insights into business practice and outcomes. The case study method is inherently suited to this type of research problem because it allows the researcher to describe the phenomena in detail, to explore and test how different theoretical constructs of the case relate to each other and importantly to create a narrative to make sense of a complex set of business and product-marketing ideas, and related InsurTech [27]–[29].

3.1 Data Sources and Interpretation

The data collection, discussion and refinement took place over one year from March 2020 to March 2021. The research was co-authored with a senior manager leading the implementation of behavioural insurance services and can be categorized as a key informant method of case data collection. In addition to interview data, access to managerial reports and information, e.g., see Table 1, and market data was granted. The management presentations provided a comprehensive and detailed overview of the overall concepts, practice and progress of behavioural insurance in the firm. Taken together, these data sources of interviews, discussion and detailed feedback and comments on the paper enabled a triangulation of documentary evidence, management reports, presentations, knowledge of key informants and market information concerning size and growth. A key part of this methodology were the discussions with the project director to test and corroborate important ideas and concepts, and to build a detailed understanding of the logic and explanatory aspects of the case study.

4. HUK-COBURG

HUK-COBURG has been a mutual insurer since 1933 and offers a range of insurance services to retail customers in Germany. Its range of insurance products includes automotive, property and casualty, accident, health, life and pensions. This case study focuses on innovations in the automotive insurance market from the novel use of Artificial Intelligence (AI), big data and related developments in digital and vehicle technologies. In 2019, HUK-COBURG had approximately 12 million customers and over 10,000 employees, with gross premiums of 7.8 billion Euros. It is one of the largest insurers for private households in Germany, market leader in motor insurance and has a strong reputation for offering fair and affordable insurance.

Automotive insurance is compulsory throughout Europe and there is intense competition to attract and retain customers. In 2016 there were over 110 million automotive policy holders, making Germany the largest country-market in Europe, with over 90 insurance competitors and 47 million insured vehicles [30]. Digital technologies and big data are transforming the automotive insurance market throughout the customer lifecycle. There is considerable innovation in the core idea of mobility such as car sharing, short-term rentals and subscription models for new cars that include insurance as part of a package. Autonomous driving has the potential to increase safety by using AI to make better driving decisions [31] and related technologies such as connected cars can provide more information to the AI system, the driver and the car's occupants [32].

InsurTech companies are also entering the market with new insurance products such as pay per use insurance, supported by digital and data analytics capabilities [33]. The automotive companies themselves also have a strong interest here. An automotive company has access to vehicle data and has the potential to develop new insurance and other value-added services based on exploiting this new form of data. However, they tend to focus on the engineering applications of telematics data rather than its marketing and insurance applications. In addition, automotive manufacturers do not all have a direct relationship with the customer, and this could be a significant marketing barrier to offering telematics insurance services.

5. Behavioural Insurance Business Model

5.1 Technical and big data analytics

Behavioural insurance is enabled by a variety of InsurTech involved in collecting driver behavioural data from many drivers at scale and in great detail, and the storage, analysis and interpretation of the data for the purposes of risk assessment, pricing, and analytics used by both the insurance firm and the drivers. The digital technology includes GPS technology, big data analytics [34] in risk assessment/driving score [16] and Artificial Intelligence (AI) [9].

Most insurance products have historically relied on the concept of risk pooling, where demographic and historical risk data is used to estimate risk, which is then reflected in the insurance premium. The objective is to ensure that total insurance premiums are greater than the total claims and operating costs to generate a profit, or at least to achieve break-even. Poor underwriting performance therefore leads to potentially significant losses, and it is crucial to focus attention on new developments and concepts that can improve the assessment of risk and potential damages.

Traditional insurance business models infer future behaviour from historical data. Age and bonus/malus variables such as no claims discount and penalties for claims are surrogate measures of driving skill and safety of an individual. As a driver builds up a track record in the form of bonus/malus classes, an insurance company can be more confident about their initial assessment. For new drivers, there is no such record, and this is one reason why new, young drivers are given a high-risk score, which is reflected in high premiums. New drivers also tend to be young, and young drivers have less experience and tend to display riskier driving behaviour. Conversely, older, more experienced drivers in a good bonus/malus class are given a low-risk assessment and low insurance premiums. Generalized linear models are a very good fit for assessing the risk of individuals using traditional data sets comprising 20-30 attributes in car insurance and are therefore prevalent in insurance risk models. Note that the use of 20 attributes or more will result in very fine and granular definition of risk groups.

A common misconception about traditional pricing models is that they are based on a set of market segments, which each contain a significant number of customers. This is not true with existing risk models, which have evolved to become highly sophisticated and granular models. However, although linear regression models can be highly targeted, for a single attribute such as age, there can be a wide variety of behaviours, which cannot be distinguished using only demographic information. A common assumption in a generalized linear model is that the attributes are independent, and the structure is multiplicative, which means that the premium for an individual customer is calculated as: $premium = average\ premium * f_1(attribute_1) * f_2(attribute_2) \dots * f_n(attribute_n)$

Imagine that $attribute_1$ is the age of the customer, $attribute_2$ is the bonus/malus class and the other attributes are related to the car, mileage, geographic region and so on. Then we see that since all customers of age 20 get the same risk factor for their age and they are usually in a bad bonus/malus class because of only 2 or 3 years driving experience, they will tend to be judged to have high risk and always pay higher premiums. Assigning a high-risk score to all 20-year-olds is unlikely to be true. Assuming that the average risk of a young drivers has been assessed accurately, the risk variance within the group of young drivers means that better drivers are probably subsidising the poorer drivers.

Behavioural risk modelling is focused on the behaviour of the individual driver and to do this effectively requires the dynamic collection and analysis of driving data taken directly from the vehicle. Conceptually this is straightforward: behavioural data tells the insurance company what is actually happening in a real-time basis; the data can be analysed to assess the driving performance, which can then be used to price the insurance premium. In practice, the implementation is more complex and difficult. HUK-COBURG started working on telematics in 2013 and launched its first product in 2016 that was based on a black box that was installed in the car. The original product was targeted at young drivers because this is a group with high risk profile and therefore high price. It was known that this group has a high variance of risk but there was very little detailed information about individual driver characteristics. The high average premium of the group was important in order to cover the costs of the telematics solution. The high-risk variance was also important to be able to realize a sensible risk differentiation. The "young driver product" offered a discount up to 30% to those drivers with a high driving score and automated emergency rescue in case of an accident. The black-box product was replaced in 2019 by a revised, cheaper technology and the product was offered to all drivers. The new technology is based on a mobile phone, a sensor tag that captures the vehicle dynamics and an app.

The logic of the product is that careful driving is rewarded with reduced insurance premiums because it results in lower accident rates so that the total value of insurance claims declines. In addition, the group of telematics drivers already has a lower risk profile and is incentivised for even better driving using interaction and feedback on driving behaviour. A further marketing advantage is that telematics drivers are less likely to switch to competitors than other drivers. The product has had a successful launch with about 360,000 customers signing up to behavioural driving in January 2021, which now accounts for approximately 10% to 15% of contracts issued at the point of contract changes such as new car, or for new customer acquisition. This dynamic share of new and renewed contracts, which could easily be increased by marketing and sales activities, suggests that the market for behavioural insurance in Germany could grow to a quarter of the automotive insurance market by 2025 – 2030. The 'big data' and highlighted statistics for HUK-COBURG customers are shown in Table 1.

Table 1. Behavioural Insurance Data Statistics
NB, 1 million = 10^6, 1 billion = 10^9

Measurement	Cumulative data for all drivers
Customer insurance contracts	354,000
App-Store downloads	487,000
Number of trips	251 million
Average distance per trip	13km.
Driving hours	69 million
GPS-position and velocity data points	144 billion
Acceleration data points	2,200 billion
Average speed	49 km/h
Maximum velocity in excess of road limit	100 km/h
Maximum velocity	230 km/h
Total data volume	459 TB
Approximate number of accidents	16,600

5.2 Business Processes and Information Flows

A schematic diagram of behavioural risk modelling using Artificial Intelligence (AI) is shown in Figure 1.

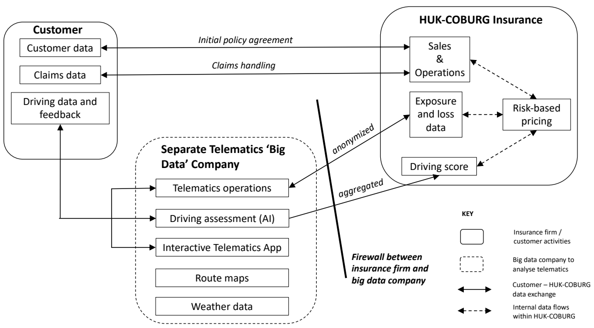

Figure 1. The information exchanges and processes involved in behavioural insurance using Artificial Intelligence (AI)

The diagram shows three separate entities: customer; HUK-COBURG insurance; and its separate 'Big Data' company, separated by a firewall to ensure data confidentiality. In the insurance company, sales manage customer acquisition and e-service, and risk-based pricing is based on a driving score received from the Big Data company. Exposure and losses are shared with the Big Data company to improve risk modelling. Note that the details of the driving behaviour are held within the Big Data company and only the aggregate driving score is given to the insurance arm of HUK-COBURG.

After the initial policy is agreed, the driving behaviour of the policy holder is tracked using the tag device and the phone app. Vehicle telematics data is transmitted to a separate HUK-telematics company and the AI algorithm performs feature extraction on the data set, e.g., acceleration and deceleration patterns, speed related to other drivers and to the speed limit, speed on different sections of roads such as corners, junctions, motorway slip roads and bends. The behaviour of the individual driver is analysed in the context of historical driving behaviour and accident data to derive a performance score, which is given back to the driver with an explanation of the score.

The dynamic assessment of risk is shared with the driver and used by the customer to proactively improve their driving behaviour and reduce the insurance premium. This means that the insurance contract becomes an experiential service. Accident detection can be integrated into the telematics solution, which is an important feature of an innovative claim steering service based on telematics data. Claims steering has a very important history for HUK-COBURG, because it operates Germany's largest automotive repair network. This integrated repair capability enables high-quality repairs for a fair price and lower repair losses is an important factor in offering market-leading insurance premiums.

5.3 Strategic Logic

The business case for launching a telematics insurance service is that it improves the risk differentiation between customers compared with the use of socio-demographic information. It is crucial to distinguish accurately between drivers based on their safe driving score because it can be shown that drivers with a low score are about ten times more likely to have an accident than those with a good score, and that the 20% of the drivers at the lower end of the score account for almost 40% of all accidents. The claims ratio for drivers with a low driving performance score is at least 2 times higher than the claims ratio for a driver with a good score. Since the premium calculated based on the traditional tariff attributes is risk adequate, for any classical customer segments based on demographic information, the claims ratio is predicted to be the same. The addition of a driving score based on telematics contributes real and substantive additional risk information for individual drivers. This improved knowledge and understanding of risk and losses is important because it enables HUK-COBURG to remain competitive in the marketplace through a better understanding of both individual and market-level risk and exposure.

In a mature market, customer retention is crucial to maintain market share. Telematics customers tend to have a higher retention rate than traditional customers, except for high-risk customers: Customers with a poor driving score are 50% more likely to leave than those with a good score, which shows that risk selection will work very well in the telematics portfolio of customers.

5.4 Ethical Framework

AI transparency and explainability is important in assessing driving behaviour and insurance pricing, and should be reflected in the design of the algorithm. But transparency and explainability will mean something very different for the respective stakeholders: The telematics data scientist of the company will need a clear and deep understanding of the algorithm and its results; they have to be able to know how certain changes in the driving style will affect the score in detail. On the other hand, the customers themselves will not understand the detail and complexity of the calculations in the algorithm.

The commercial value of the Intellectual Property (IP) of the AI algorithm may limit the company's ability to share highly detailed explanations of how it works. The driver will also not know "precise rules to obey" since only obeying rules such as "no speed excess" does not make you a good driver and can even result in dangerous driving situations, because after all, the important point is that driving behaviour is adapted to the individual driving situation and forward-looking driving is key to safety. So, for the customer, transparency and explainability means that they can experience the effects of different driving styles on their driving score. It also means getting information and feedback about their score, and how their driving behaviour can be improved.

An important point here is that it's perfectly valid for an insurance company to use opaque algorithms in some specific aspects of an AI system, e.g., deep learning techniques for determining speed limits on roads, or for detecting risky driving manoeuvres such as overtaking, from complex driving data. It is not necessary to disclose the exact mechanisms for how these are calculated to the consumer – it is sufficient to identify these as significant events that affect their driving score.

The development of a telematics driving score is based on a set of clear principles: it should be based on scientific and mathematical reasoning and models; only behaviour counts towards the score; no use is made of socio-demographic factors; drivers are not penalised for events beyond their control, e.g., whether their driving is predominantly at night or in inclement weather; and it is an optional method for determining risk and the insurance premium, and customers can continue to use the traditional model. The data from a driver's journey is a continuous stream of information that contains the GPS location, forward and lateral acceleration and velocity of the vehicle. This data is combined with map information to give information about the journey characteristics, including type of road and speed limit, traffic information and weather. Speed has a clear and direct influence on the driver's score, so it is vital that the algorithm has accurate information. Speed limits are defined on maps, but these may change, for example because of road works, and HUK-COBURG put a lot of effort into ensuring accurate speed limit data by building their own speed-limit maps that are based on their own community of drivers.

The driving score algorithm is based on a set of driving features that are pre-defined and based on the concept of safe driving. The most important basic features are speeding above the designated speed limit, rapid acceleration, rapid deceleration, and fast cornering. More complex features combine different elements of information, e.g., rapid acceleration above a certain speed, or speeding at night or in poor weather conditions. The basic features of speed and acceleration can also be related to other data such as traffic congestion. Note that a driver is not penalised for driving at night per se but speeding at night is judged to be riskier behaviour than speeding during the daytime. Complex events that can also be inferred from the data stream include risky overtaking, a racing start to a journey and stalling the car. Features that relate to the nature or purpose of the journey, e.g., a visit to a Doctor's surgery, the choice of a grocery supermarket or private habits, are never used, even if they could, theoretically, be used to differentiate risk between customers. The algorithm does not discriminate against customers on the basis of time, weather, or geographic region as individual factors, but does use this information when a driver displays risky driving behaviour that could be exacerbated by dangerous road conditions from wet weather or reduced visibility from night-time driving.

The driving score is computed based on a machine learning analysis of the features described above. Speeding above a limit and high levels of acceleration and deceleration, are graded according to their severity. For example, 10 kmh^{-1} above the speed limit is a class 1 event, 11 kmh^{-1} is a class 2 event, 13kmh^{-1} is a class 3 event, and so on. A similar logic is used to classify sharp linear and lateral acceleration. The score is not a simple weighted score of performance in different areas, say speed, acceleration and breaking behaviour, because this could result in a relatively high score even though a driver has very risky behaviour in one area and apparently safe behaviour in others. Highly risky behaviour in just one area will therefore result in a low score. To achieve a high score requires consistently safe driving behaviour in all areas. De facto, the driving scores correlate with accidents and are judged to a better and more objective assessment of risk than traditional methods.

An analysis of a journey from Oberhof to Coburg is shown in Figure 2 where the driver scored a very low '9' for their driving performance. This route is 67 km. and normally takes around 50 minutes by car. In this case the driver took 45 minutes. On the left side a map with the major events that counted against the driver are shown with some brief commentary. Two segments of the trip are expanded to show more detail. At the start of the journey, the driver accelerated hard, which is termed a 'kickstart' and then raced through a series of bends measured by the level of centripetal force on the car. The second major incident is sharp braking, because another car on the highway suddenly changed the lane, measured by the magnitude of deceleration, in this case 6ms^{-2}. The third incident was sharp braking just before the exit road, which indicates poor anticipation or last second decision-making, both of which are potentially risky driving behaviour. In contrast, a driver with just one notable event, high lateral acceleration on a slip road, a score of 87 was achieved.

An evaluation of the driving score, which is inversely proportional to the risk of having an accident, is the fairest method of determining insurance premiums because it does not unfairly discriminate on socio-demographic factors so that all drivers are treated equally. The system is also designed so that it does not penalise drivers who for example must drive at night-time, which is inherently riskier for the population as a whole, nor does it increase the risk factor for bad weather conditions. Of course, speeding at night will have an adverse effect on driving score and this is something that can be avoided by all drivers, regardless of whether they must work at certain times or not.

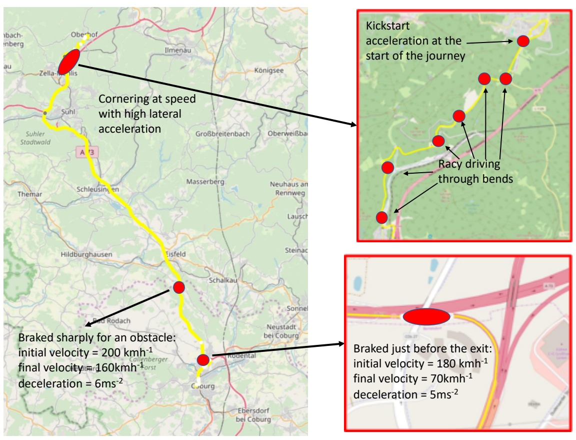

Figure 2. Analysis of driving performance using behavioural data

5.5 Regulatory Context

The use of all behavioural driving data linked to an individual is subject to EU General Data Protection Regulation (GDPR). An overview of HUK-COBURG's approach to and compliance with GDPR is shown in Table 2.

Table 2. GDPR principles and related HUK-COBURG activities

GDPR Principles	HUK-COBURG Activity
Lawfulness, fairness and transparency	The data is analysed in such a way as to ensure compliance with insurance regulations and to only use features that inform risk that are objective, fair and open to interrogation, i.e., they are transparent. Customers can request access to their own data.
Purpose limitations	Data is only used to support and facilitate the telematics product and pricing, including related statistical purposes, i.e., to analyse and evaluate individual driver risk. Data is not shared with any third parties, i.e., it is not sold to be used for other purposes. Use of the data for other purposes provided by the HUK-company group, such as offerings of car service would need explicit consent of the customer, but consent to such offerings would not be necessary in order to use the telematics pricing product.
Data minimisation	Only data that relates to driving behaviour is used to assess risk, e.g., acceleration, velocity, deceleration and cornering speed. Destination data is not included in the analysis and there is no effort to infer the purpose of journeys, e.g., to visit a Doctor's surgery, to see a friend or to visit a particular restaurant.
Accuracy	The data collection devices are calibrated and the models to assess risk are continually revised and refined to make them more accurate in the light of new information from customer driving data, accidents and loss data.
Storage limitations	Customers have the right to have their personal driving data erased.
Integrity and confidentiality	Clear policies and actions to ensure that the data is held securely. In addition, the data is held by a separate company to create a 'Chinese Wall' between the traditional insurance company and the personal, behavioural driving data
Accountability	The AI algorithm and associated use of customer data is transparent to customers and supported by a clear set of data protection principles and organisational systems

5.6 Implementation Challenges

The implementation challenges involved in behavioural insurance range from the technical issues associated with collecting an enormous number of new types of big data such as GPS location, acceleration and route maps to the adoption of the new service by customers who may be concerned about the effects on their premium or privacy issues such as the potential for surveillance. The range of challenges include marketing, AI, the definition of safe driving, customer feedback, transparency and explainability, digital technology design, ethics and data privacy, and the business case for telematics are described in more detail below. The AI challenges are examined in more detail. Beyond the actual technology design, the implementation philosophy is summarised by the following aphorisms: the solution will never be perfect so there is a need for continuous improvement; the quality of the system is monitored to identify faults and areas for improvement; changes in technology should be anticipated where possible so that the company can react with relevant and suitable changes to the digital design of the product; a culture of testing to identify and solve problems should be the norm; the AI algorithm to develop a driving score is highly sophisticated, therefore the customer needs to collaborate in the evaluation of their driving, because feedback is essential.

As part of the continuous improvement and testing, HUK-COBURG operate a test fleet of approximately 1,000 cars to gain valuable feedback and comments from its test drivers. Once customers are signed up to use the driving app it is important to achieve an excellent level of customer satisfaction to achieve a high level of customer retention. Feedback from the App 'HUK Mein Auto' averaged 4.0 / 5.0 based on over 4,000 customer reviews. Especially in the starting phase of the product, 20 full-time staff offered customer support for telematics and dealt with a range of technical and policy questions and issues. Since then, support processes have been significantly reworked to be more digital and less staff-demanding, while at the same time satisfying customers' needs.

5.7. The Data Flywheel Concept

Business model value creation must nearly always include the customer and possibly a wider network of inter-related organisations, e.g., a value chain, a virtual organisation, a group of team members from separate firms or a simple firm-customer relationship [23]. Business models explicitly include this capability by describing and analysing business activities from a value-system viewpoint, rather than drawing hard organisational boundaries. That is, the boundary of the system is defined by the researcher/modeller and is dependent on the business and technology foci of interest. This means that in addition to the firm's internal business activities it is possible, and arguably desirable, to incorporate customers, suppliers, economic partners, technology partners, entrepreneurial firms, business customers and individual consumers into business model design and thinking. In a technology-intensive business model, or where the purpose of the research is to focus on the role, implementation and effects of a digital technology, a useful approach is to model the business activity and relationships between activities and entities (e.g., organisations, individuals, technology firms) as data flows. This is particularly important in a big data context where business model transformation is inextricably bound up with business transformation [5][35].

Telematics specifically and digital technology as a general-purpose technology, have created a data-rich environment around automotive vehicles that is changing the historical rules and norms of engagement between insurance firm and their customers – this is termed a market discontinuity. Market discontinuities are often driven by fundamental shifts in technology, e.g. the Internet and e-commerce has allowed new entrants into retailing, bypassing traditional barriers to entry, the launch of 3G services made it possible for new mobile phone networks to enter a range of national markets with predominantly data services rather than call-based services and this was arguably the start of the rapid growth in the use of apps that could exploit the increased processing power of mobile phones and make use of the widely available data packages that came bundled with service contracts.

The data flywheel business model concept for HUK-COBURG's behavioural insurance product is shown in Figure 3. This model takes a dynamic approach that captures the evolutionary nature of AI algorithms and big data in an insurance market context. The diagram shows the content of the individual business activities (e.g., an event such as market discontinuity, an action such as develop behavioural insurance product, experiment as part of the R&D, acquire new customers), and the inter-relationships between them, i.e., the structure of the business model. This is a dynamic model because it partly captures the passage of time and therefore evolution, vide the circular connections between activities within the area that is labelled 'AI data flywheel' [36] and also indicates the possible emergence of a new kind of insurance digital platform [37].

In the case of AI and data-intensive services, the data flywheel can potentially be an important competitive advantage [38], which stimulates growth as a virtuous circle, and therefore makes it attractive to be the first or at least an early innovator to a market created by a technology discontinuity. By experimenting at an early stage, HUK-COBURG acquired new customers and crucially, relevant data on which to model risk and relate them to outcomes, in particular loss and accident data. This in turn improved the AI model, which can then be further enhanced, e.g. by synthesising other data sets into the model such as weather patterns, individual routes, and web-cam data.

The AI data flywheel is a cycle of improvement that makes the product better, improves new customer acquisition and retention of customers who might have switched to competitors and builds a barrier to entry based on AI knowledge and big data. The growth in the customer database improves the quantity and quality of data and produces opportunities to cross-sell related insurance products. The benefits are enjoyed by both the insurance firm and its customers, and the business value is co-created through the processes of contributing big data, use of the data analytics for risk assessment and reduction, and in refining the AI algorithm. The concept of co-creation of business value is an important concept from marketing [39] and is a crucial element of most AI data flywheels where the customers continue to contribute data and enjoy the benefits of a continuously improving product [40].

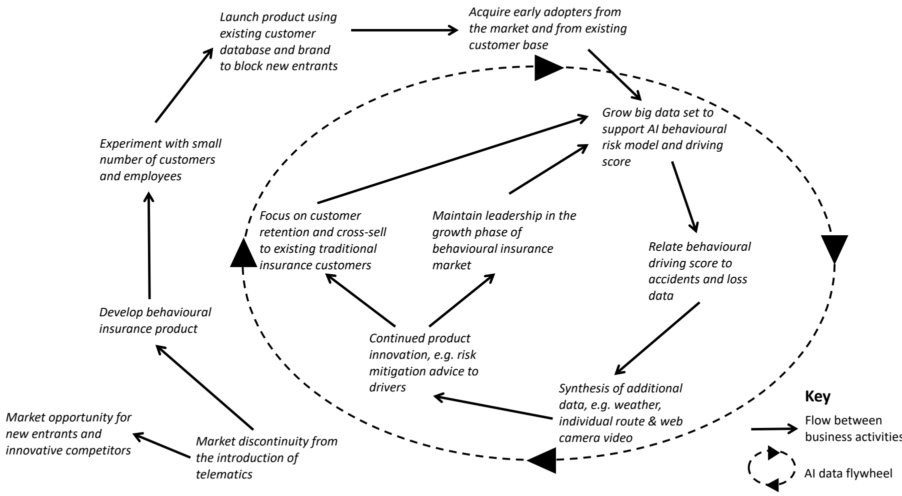

Figure 3. The AI Data Flywheel Effect in the Behavioural Insurance Business Model

The AI data flywheel and the role of data throughout the customer lifecycle mean that an insurance firm's ability to generate big data sets, build AI systems and exploit the business value from big data, are important areas of competitive differentiation in the evolution of innovative business models [41].

6. Conclusions

New competitors, the availability of geo-spatial data from GPS and vehicle telematics, and trends in mobility means that insurance incumbents must respond and embrace digital transformation and novel business models and technologies that take advantage of new forms of big data such as geo-spatial data, and advanced analytics. The concept of risk is central to all forms of insurance and the combination of GPS data, vehicle telematics and big data analytics create brand new methods to model and understand risk in automotive insurance markets and provide mechanisms to actively mitigate and reduce the risk of accidents.

Behavioural insurance creates dynamic risk profiles in a market of one. The nature of the insurance service changes from a static product to one where the customer and insurance firm engage in an interactive and ongoing dialogue – in this context, the insurance contract becomes an experiential service that is designed to improve the outcome for both parties: safer driving behaviour and fewer accidents for customers; more accurate risk profiles and lower pay-outs for the insurance firm.

Successful insurance firms must have leading capabilities in digital and organisational transformation, data science and analytics to compete effectively against InsurTech and embrace digital first business concepts to launch and grow next-generation insurance services. The continuing development and evolution of vehicle telematics, AI technology and spatial data analytics will exacerbate the technical implementation challenges of new business models and create new strategic, ethical and regulatory problems.

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