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Digital Transformation and Innovation in the Insurance Sector: Processes, Technologies, and Challenges

The digital transformation of the insurance sector improves risk assessment, pricing, distribution, and claims management. Key technologies driving these changes include artificial intelligence (AI), machine learning (ML), big data analytics, and automation. These advancements primarily drive process innovation, aligning with Barras's reverse innovation cycle rather than traditional product innovation.

The authors show that key technologies such as telematics, the Internet of Things, predictive analytics, and robotic process automation streamline operations and improve customer experience. However, challenges remain in ensuring AI transparency and interpretability. While digital transformation is still in its early stages, its continued development will shape the industry's efficiency, competitiveness, and regulatory landscape.

Keywords: Digitalisation of insurance, process innovations, AI in insurance, Barras's reverse innovation cycle, big data in insurance

Introduction

The insurance sector, traditionally regarded as one of the more conservative branches of the financial industry, is undergoing a profound transformation driven by digital transformation and technological advancements. The increasing adoption of artificial intelligence (AI), machine learning (ML), big data analytics, and automation is reshaping how insurers assess risk, price policies, process claims, and interact with customers. These innovations are not only streamlining operational efficiency but also redefining business models and customer expectations.

The rapid development of digital technologies is a response to several key factors. First, shifting consumer behaviour – particularly among younger generations – has increased demand for digital-first insurance solutions, including on-demand and usage-based insurance models. Second, advancements in data collection, facilitated by Internet of Things (IoT) devices, telematics, and wearable technologies, allow for more precise risk assessment and personalised pricing strategies. Finally, regulatory changes and competitive pressures are pushing insurers to modernise their processes to remain relevant in an evolving market landscape.

Despite these advancements, the insurance industry's innovation trajectory follows a different pattern than that of manufacturing and other financial services. While product innovation has historically played a central role in industrial innovation cycles, the insurance sector primarily experiences process-driven innovation, aligning with Barras's reverse innovation cycle. Process improvements in underwriting, pricing, distribution, and claims management often precede the development of entirely new insurance products, a phenomenon that distinguishes the sector's digital evolution.

This article examines the current state (in 2025) of digital transformation in insurance, exploring key technological trends, their impact on core insurance processes, and the challenges associated with the adoption of AI. By analysing recent innovations in underwriting, pricing, claims management, and distribution, we assess the industry's position within the broader framework of financial services innovation. Additionally, we address the regulatory and ethical considerations surrounding AI-driven decision-making, emphasising the need for transparency, explainability, and consumer trust in the digital insurance landscape.

Through this analysis, we aim to provide a comprehensive overview of how digital transformation is shaping the insurance sector and to identify areas for further research and development. Understanding these dynamics is crucial for insurers, regulators, and policymakers seeking to navigate the opportunities and risks presented by the ongoing technological revolution in insurance.

1. The Innovation Cycle in Financial Services

1.1. Innovation and Innovativeness

Innovativeness is a broadly defined concept in the literature, and the term *innovation* has been in use since the late 19th century to describe something extraordinary[1]. One of the first economists to define innovativeness and to demonstrate that the innovation process is crucial for economic development was Joseph A. Schumpeter. In his book *The Theory of Economic Development* and subsequent works, Schumpeter described economic growth as a historical process of structural change largely driven by innovation. He identified five types of innovation[2]:

1. Vide: Schumpeter J.A., Grzywicka J. and Górski J., *Teoria rozwoju gospodarczego*, PWN, Warszawa 1960, p. 104; Niedzielski P. and Rychlik K., *Innowacje i kreatywność,* Wydawnictwo Naukowe Uniwersytetu Szczecińskiego, Szczecin 2006, p. 19; Janasz W. and Kozioł-Nadolna K., *Determinanty działalności innowacyjnej przedsiębiorstw*, PWE, Warszawa 2007, p. 14.
2. Vide: Schumpeter J.A., *The theory of economic development: an inquiry into profits, capital, credit, interest and the business cycle*, Harvard University Press, Cambridge 1934; Idem, *Business Cycles: A Theoretical, Histo-*

1. The introduction of a new product to the market or a new variety of an existing product.
2. The application of new production or sales methods (previously untested in the industry).
3. The opening of a new market (one where the given industry was not previously represented).
4. The acquisition of new sources of raw materials or semi-finished products.
5. A new industrial structure, such as the creation or destruction of a monopolistic position.

Schumpeter argued that innovativeness is the fundamental driving force behind competitiveness and economic dynamics[3]. He claimed that anyone seeking profits must innovate, which leads to a reallocation of existing resources within the economic system[4]. He also positioned innovation at the core of economic change, introducing the concept of *creative destruction* in his book *Capitalism, Socialism, and Democracy*. According to Schumpeter, innovation is the process of industrial mutation that incessantly revolutionises the economic structure from within, incessantly destroying the old one, incessantly creating a new one[5].

However, these definitions primarily refer to processes in manufacturing rather than financial services. This may be because there has been significantly less research on innovation in the financial sector than in the industrial sector. Nevertheless, all five types of innovation identified by Schumpeter can be applied to the analysis of innovation in financial services. Given the specificity of services – particularly insurance – the innovation trajectory in services follows a different path than in manufacturing, as described by Barras. On the one hand, the insurance sector itself can be innovative; on the other, it should support innovation in other industries by reducing their risk aversion.

Contemporary research on innovation focuses almost exclusively on experience from the manufacturing industry. It emphasises the technological aspects of innovation and suggests that these are exogenous determinants of industry structure and competitiveness. Financial innovations, until recently, remained a largely unexplored area of economic research. One of the first scholars to examine innovation in financial services was William L. Silber. Since 1952, Silber has studied monetary innovations, including new credit instruments and investment contracts in U.S. capital markets[6].

A rare example of research related to innovation in insurance is a study conducted by L. Laeven, R. Levin, and S. Michalopoulos[7]. These authors modelled financial decision-making in the sector, evaluating the level and degree of innovativeness among entrepreneurs based on Schumpeter's definition of innovation, which stems from the introduction of new products to the market. Their research indicates that the issue of innovation has been examined within the financial sector (primarily banking) but analysed through the lens of how offering new and profitable products in the production sector could also contribute to profit maximisation in financial services. Consequently, they questioned whether financial innovation (understood as various improvements that facilitate

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rical and Statistical Analysis of the Capitalist Process, *Vol. 2*, McGraw-Hill, New York 1939; Idem, *Capitalism, Socialism and Democracy*, 5th edition, George Allen and Unwin, London 1976.

3. Cf.: Porter M.E. and Stern S., *The New Challenge to America's Prosperity: Findings from the Innovation Index,* Council on Competitiveness, Washington, DC 1999; Hanush H. and Pyka A., *Elgar Companion to Neo-Schumpeterian Economics*, Edward Elgar Publishing, Cheltenham, UK, Northampton, MA 2007, pp. 1–18.
4. Vide: Schumpeter J.A., *The Theory*, op. cit.
5. Vide: Idem, *Capitalism*, op. cit.
6. Silber W.L., *The Process of Financial Innovation*, 'American Economic Review', 1983 vol. 73, issue 2, pp. 89–95.
7. Laeven L., Levine R. and Michalopoulos S., *Financial innovation and endogenous growth*, 'Journal of Financial Intermediation', 2015 vol. 24, pp. 1–24.

the selection of potential clients, such as new financial reporting procedures required from innovative entrepreneurs seeking funding) is a necessary condition for sustainable economic growth.

Another study particularly interesting from the perspective of differences in the innovation process between services and manufacturing was conducted by Barras[8]. His research inspired the authors of this article to reflect on modern innovation in the insurance industry. Since the 1960s, Barras has studied the impact of IT on financial services, leading him to develop a theory of innovation in financial services based on a reversal of Schumpeter's product cycle theory. Table 1 presents the so-called *reverse innovation* cycle in services proposed by Barras.

Table 1. The reverse innovation cycle in services according to Barras

A: The product cycle in manufacturing
1. *Introductory/take-off phase* Major product innovation clusters during the establishment of new industries.
2. *Growth phase* Standardisation of products – falling unit costs – competition shifts to process innovations to improve the decreasing range of products.
3. *Maturity phase* Markets nearing saturation – shift towards more incremental process improvements to reduce unit costs.
4. *Transition phase* Established technology/industries become increasingly obsolescent/vulnerable to competition from new technologies/industries.
B: Barras's reverse product cycle in services
1. *Improved efficiency phase* Initial investment in new technology (IT) by established firms leads to incremental process innovation to improve the efficiency of delivering existing products – to boost labour productivity, reduce costs.
2. *Improved quality phase* More radical process innovation to improve the effectiveness/quality of existing products.
3. *New products phase* Competition shifts to product differentiation; new firms, new products, new markets.

Source: Barras R., *Towards …*, op. cit., pp. 161–173; Idem, *Interactive innovation in financial and business services: the vanguard of the service revolution*, 'Research Policy', 1990 vol. 19, pp. 215–37.

According to Barras, there is an interaction between new technologies in capital goods industries (IT manufacturers) and innovations in service implementation industries. This interaction occurs through two product cycles operating in opposite directions, causing production innovation to shift from a product-focused approach to a process-focused one. In the case of services, innovation follows the opposite pattern. As product innovation in the manufacturing sector declines, it accelerates in services.

1.2. Innovativeness in the Insurance Sector

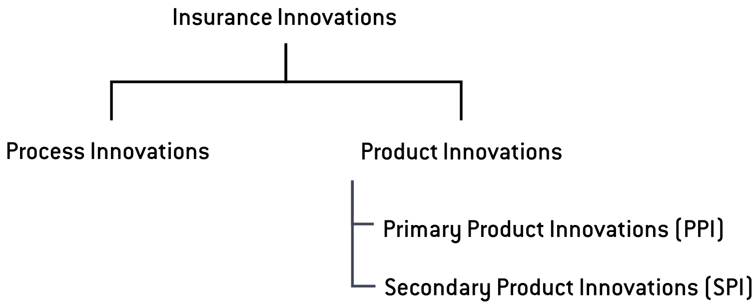
A key question arises: is the insurance industry today innovative in terms of the Barras' cycle described above? To answer this, it is essential to distinguish between two types of innovation. Pearson identified two types of innovation in financial services: **product innovations** and **process**

8. Barras R., *Towards a Theory of Innovation in Services*, 'Research Policy', 1986 vol. 15, pp. 161–173.

innovations[9]. Process innovation is defined as a change in the way existing insurance lines are developed, such as improvements in risk assessment (e.g., new insurance contract terms, new classifications of existing risks), marketing, or overall organisational improvements. Product innovations, on the other hand, can be further categorised into two groups. The first concerns the development of new products that cover new risks. This is referred to as **primary product innovation** (PPI) and depends on the technological integration of the external economy. The second type – **secondary product innovation** (SPI) – involves the creation of new products for existing risks. Secondary product innovations, therefore, depend solely on process innovations within the insurance sector and do not require any external stimuli.

The types of insurance innovations identified by Pearson are illustrated in Figure 1.

Figure 1. Types of insurance innovations



Source: Own elaboration based on Pearson R., op. cit., pp. 243–244.

Product innovations related to the emergence of new risks are significantly more sophisticated compared to process innovations and secondary product innovations. This is particularly true for life insurance, which is often perceived as a traditional product. In the past, there were considerably more innovations in property and personal insurance products, especially at the turn of the 18th and 19th centuries. Some of these innovations are presented in Table 2.

Table 2. Product innovations in insurance in selected countries, 1720–1900

Type of Insurance	UK	Germany	Austria	France	Belgium	US	Switzerland
River transport		1765	1768	1838		1849	
Credit	1820	1856	1837				
Treaty reinsurance	1824	1824	1845	1820	1820		
Fidelity guarantee	1840					1876	
Hailstorm	1840	1797	1828	1802		1870	
Livestock	1844	1720	1840	1805	1836		
Burglary	1846	1850	1865			1878	1898
Personal accident	1848	1853	1877			1864	
Traveler's luggage	1851					1870	
Plate glass	1852	1861	1867	1829		1874	

9. Pearson R., *Towards an Historical Model of Services Innovation: The Case of the Insurance Industry, 1700–1914*, 'Economic History Review', 1997 vol. 50, no. 2, pp. 235–256.

Type of Insurance	UK	Germany	Austria	France	Belgium	US	Switzerland
Boiler	1854					1866	
Engineering	1858						
Windstorm/tornado		1899		1887		1861	
Engine	1872						
Public liability	1875			1829			
Employer’s liability	1880	1871			1848		
Cycle	1883			1890			
Parcel post	1883						
Elevator/lift	1888						
Mortgage guarantee	1888						
License	1890						
Loss of salary		1892				1892	
Automobile	1896	1899					
Professional indemnity	1896						
Electrical machinery	1897						
Property owner's indemnity	1897						

Source: Pearson R., op. cit., p. 239.

An example of a certain type of innovative activity in PPI is the creation of unit-linked life insurance, which first appeared in the United States in 1952 and in the United Kingdom in 1957. However, its impact on the markets became evident only in 1962–63[10]. A similar example can be found in the products developed during the communist era in Poland. During this period, group insurance policies emerged and became highly popular. Another notable development was the introduction of child endowment insurance, a policy in which the child is the insured party, but the coverage extends to the lives of the parents[11]. These examples of insurance products introduced during communism illustrate the influence of cultural expectations on innovation within the insurance sector.

As of the early 2020s, it is quite difficult to find examples of PPI in the insurance sector, as defined by Pearson. Some studies and analyses suggest that insurance markets are not particularly innovative, especially in terms of product development[12]. However, certain initiatives related to the creation of new insurance products have emerged. One relatively novel example is the ‘Taxpayer’ policy by Allianz[13], which provides protection against tax disputes. This insurance product mitigates the risk of tax-related litigation.

Overall, insurance markets seem to be positioned somewhere between the first and second phase of Barras’ innovation cycle. However, in certain business lines, innovation is significantly more advanced than in others. A good example is trade credit insurance, suggesting that this segment is entering the second phase of the cycle.

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10. Melville G., *The unit-linked approach to life insurance*, ‘Journal of the Institute of Actuaries’, 1970 vol. 96, issue 3, pp. 311–367.
11. Cf. Stroiński E., *Ubezpieczenie na życie*, Wyższa Szkoła Ubezpieczeń i Bankowości: ‘Lam’, Warszawa 1996.
12. Śliwiński A., Karmańska A., Michalski T., *European Insurance Markets in Face of Financial Crisis: Application of Learning Curve Concept as a Tool of Insurance Products Innovation – Discussion*, ‘Journal of Reviews on Global Economics’, 2017 vol. 9, p. 409.
13. Official Polish name is *Podatnik*; Allianz, *Ubezpieczenie Allianz Podatnik*, https://www.allianz.pl/pl_PL/dla-firm/dla-przedsiebiorstw/ochrona-prawno-podatkowa/allianz-podatnik.html (Dec 7, 2024).

The key question remains: when (or if) markets will transition into the third phase and whether we can expect PPI to emerge. This is particularly relevant given the rise of new risks, such as nanotechnology risks and cyber risks, which affect both individuals and the broader economy.

Another confirmation of the current stage of innovation in the insurance sector can be found in a brief analysis of the most innovative start-ups in the insurance industry. The majority of these start-ups primarily focus on process innovations, while product innovations play a secondary role (see Table 3).

Table 3. Most innovative start-ups in the insurance industry

Start-up Name	Year Founded	Main Idea	Country	Process Innovation	Product Innovation
QuanTemplate	2011	Utilises machine learning and big data analytics to help insurance professionals navigate digital transformation trends.	UK	YES	–
Bought by Many (now ManyPets)	2012	Groups clients with specific insurance needs and offers customised products tailored to them.	UK	YES	–
Shift Technology	2014	Offers AI-driven SaaS solutions for fraud detection and cybersecurity in the insurance sector.	France	YES	–
Zipari	2014	Develops customer experience and engagement tools for health insurers.	USA	YES	–
Flock	2015	Builds a risk analysis platform based on large datasets obtained from drones. On-demand insurance.	UK	YES	YES – SPI
Clark	2015	Insurance platform offering transparent, affordable, and comprehensive protection.	Germany	YES	–
Ottonova	2015	Health insurance product distributed through a digital platform.	Germany	YES	–
Lemonade	2015	AI-based bot for personalised insurance. Clients can be insured in 90 seconds and receive payouts within 3 minutes.	Germany	YES	–
Zego	2016	Offers hourly insurance policies for scooter drivers.	UK	YES	–
Zeguro	2016	Reduces cyber risk for SMEs.	USA	YES	–
Wrisk	2016	Provides transparent insurance processes with a focus on partnerships, offering services through mobile apps.	UK	YES	–
Ondo	2016	Specialises in sustainable risk reduction, working with home insurers globally to tackle water damage issues.	UK	YES	–
Next Insurance	2016	Digital-first insurance company focused on small businesses, offering customised policies online.	USA	YES	YES
Insoore	2017	Integrates insurance with fleet management processes.	Italy	YES	–

Start-up Name	Year Founded	Main Idea	Country	Process Innovation	Product Innovation
FloodFlash	2017	Uses algorithms to determine personalised pricing, enabling the creation of customised, competitive flood insurance policies for high-risk locations worldwide.	UK	YES	YES (Claims are settled based on objective sensor data from the FloodFlash client.)
Inshur	2017	Digital insurance platform for drivers.	USA	YES	–
Dinghy	2017	Flexible, on-demand professional indemnity insurance for freelancers and gig workers.	UK	YES	YES
CoVi Analytics	2017	AI-driven risk and compliance management platform for insurers.	UK	YES	–

Source: Based on Board of Innovation, *10 Innovative Startups in the Insurance Industry*, https://www.boardofinnovation.com/blog/10-innovative-startups-in-the-insurance-industry/ (Dec 7, 2024) and Bennett R., *The top 10 most innovative and disruptive Insurtech companies*, https://www.information-age.com/the-top-10-most-innovative-insurtech-companies-15788/ (Jan 31, 2025).

2. Digital Transformation and Its Significance

Between 2015 and 2025, the way we live, work, and communicate has been transformed by the rapid advancement of technology. The development of digital devices and platforms has made the world more interconnected, and businesses are increasingly leveraging digital technologies to streamline their operations and deliver services. **Digital transformation** is not merely a short-term trend but a key factor shaping operational strategies and business competitiveness in the 21st century. Service innovation processes are at the core of this transformation.

The growing importance of data has led to the rise of **data analytics** and **data-driven learning**, which have become key competitive advantages for many firms. Digital technologies have become pervasive in everyday life, enabling global collaboration and creating new opportunities[14]. While digital transformation has had a profound impact on all aspects of life, its effects on the economy remain difficult to measure[15].

Constant digital connectivity demands greater interaction with customers and collaborators, and access to technological resources is increasingly replacing traditional notions of ownership. Although digital technologies may be perceived as disruptive, they often enhance the customer experience by bridging the physical and digital worlds and focusing on user needs rather than

14. Borges M., Chesbrough H. and Moedas C., *Open innovation: Research, practices, and policies*, 'California management review', 2018 vol. 60, issue 2, pp. 5–16.
15. Brynjolfsson E. and Collins A., *How Should We Measure the Digital Economy?*, 'Harvard Business Review', November–December 2019, pp. 140–148.

the technology itself[16]. The scope of **digital technologies** is vast, with new tools continuously driving positive change in business development.

Since around 2018, the insurance industry has undergone a profound transformation, driven by the emergence of innovative technologies and disruptive business models. Insurtech exemplifies a paradigm shift in how insurance companies operate, leveraging advanced technologies to enhance various components of the insurance value chain. From customer acquisition and underwriting to claims processing and risk management, insurtech is reshaping industry practices and redefining the roles of insurers, intermediaries, and policyholders.

Insurtech, a term derived from the combination of insurance and technology, refers to the application of innovative technologies in the insurance sector to improve operational efficiency, customer experience, and the transformation of traditional insurance practices. It leverages technologies such as artificial intelligence, machine learning, big data analytics, blockchain, and the Internet of Things to revolutionise various aspects of the insurance industry. Insurtech refines process innovation by introducing automation, digital personalisation, and efficiency-driven underwriting, consistent with historical patterns of process innovation in insurance. Through technology, insurers can enhance underwriting processes, automate policy administration, implement advanced risk assessment models, and develop innovative products tailored to specific customer segments. Insurtech promotes a data-driven approach, enabling insurers to leverage data from various sources, such as social media and wearable devices. This data-centric model facilitates more accurate pricing, improved risk management, and the ability to offer proactive and preventive services.

One notable application is telematics, which allows insurers to determine insurance premiums based on a driver's behaviour and driving style. Similarly, wearable devices such as smartwatches collect health-related data, influencing the calculation of insurance premiums based on an individual's lifestyle and health indicators. Insurtech companies are also introducing solutions such as chatbots, artificial intelligence, machine learning, and blockchain, which facilitate efficient information exchange and foster trust. An innovative application in the industry is the use of drones, which enable rapid property assessments and remote measurements. Additionally, insurtech firms offer digital brokers who provide insurance advisory services through mobile applications[17].

Insurtech is beginning to reshape the global insurance market by introducing innovative digital products and entering traditionally dominant business lines. To survive in the digital era, insurers must enhance customer service, offer innovative products through digital channels, and collaborate with, or acquire, insurtech firms. This dynamic presents both competitive threats and opportunities for business partnerships. Insurtech innovations enable insurers to expand coverage options, introduce new products, streamline claims processing, and reduce operational costs. However, fully leveraging emerging technologies requires a shift in corporate culture and the adoption of a new business philosophy. Moreover, insurance regulators worldwide must adapt to technological advancements to ensure policyholder protection and fair competition[18].

16. Furr N. and Shipilov A., *Digital doesn't have to be disruptive: the best results can come from adaptation rather than reinvention*, 'Harvard Business Review', 2019 vol. 97, issue 4, pp. 94–103.
17. Cf.: Cortis D. et al., *InsurTech* in: *Disrupting finance: FinTech and strategy in the 21st century*, eds. T. Lynn et al., Palgrave Pivot, Cham 2019, pp. 74–77; Chmilowski A., *Insurtech–zmiany tradycyjnych ubezpieczeń w kontekście ekonomii współpracy*, 'Kwartalnik Naukowy Uczelni Vistula', 2019 no. 4(62), p. 61.
18. Koprivica M., *Insurtech: challenges and opportunities for the insurance sector*, 'Proceedings of 2nd International Scientific Conference on Recent Advances in Information Technology, Tourism, Economics, Management

In conclusion, the digital transformation in the insurance sector is still in its early stages. AI-driven solutions, telematics, blockchain, and social media are shaping the future of the industry. These transformations are fuelled by the rise of a collaborative economy, where innovation thrives on connectivity and shared resources. Just as historical innovations in insurance integrated finance with evolving economic structures, modern digital transformation integrates insurance, technology, and business models, allowing for customised financial solutions. Traditional insurers must adapt to the challenges of the collaborative economy and leverage synergistic partnerships with insurtech firms to ensure mutual benefits for all stakeholders in the insurance ecosystem[19].

3. Digital Transformation in Insurance – Selected Areas

3.1. Product Development

Although the insurance sector has long been considered more traditional than other financial market segments, such as banking and capital markets, since the late 2010s, it has also begun to embrace digital technologies and innovations. This shift is driven by multiple factors. Undoubtedly, the insurance industry – including insurers, intermediaries, and other market institutions – is increasingly leveraging digital applications in product development, facilitating insurance coverage through technological solutions from both the supply and demand sides. While such trends were already emerging, the COVID-19 pandemic and its associated implications significantly accelerated the digitalisation and technological transformation of the sector.

Additionally, the industry is increasingly utilising both internal and external databases (including big data), allowing for better product customisation and more precise premium pricing. Finally, the growing proportion of younger users, who regularly engage with digital applications and technological innovations, has influenced the sector's transformation. These tech-savvy consumers demonstrate a greater willingness to access insurance services online, reinforcing the need for regulatory frameworks that keep pace with changes in both the physical and digital realms. In the realm of insurance products, the digital transformation of the insurance sector is primarily reflected in the increasingly widespread adoption of traditional insurance offerings, such as motor, health, and home insurance, while leveraging technological innovations to enable greater personalisation and more precise pricing models. These advancements have given rise to **digital insurance**, where coverage can be tailored dynamically based on data-driven insights. Furthermore, the progress of digital and technological transformation has not only enhanced existing products but has also facilitated the emergence of entirely new insurance solutions that were virtually non-existent until recently. Notable examples include cyber insurance, which addresses financial risks associated with cyber threats, and drone insurance, developed in response to the growing use of unmanned aerial vehicles in both the commercial and private sectors. In digital insurance, two primary conceptual models can be distinguished: **on-demand insurance** (ODI) and **usage-based insurance** (UBI).

In the case of ODI, the core idea is that the customer retains full control over when their assets are insured. By using a mobile device, policyholders can not only activate coverage independently but also terminate protection as needed, providing maximum flexibility. Typically, activation is facilitated

and Agriculture – ITEMA', Graz, Austria 2018, pp. 622–623.

19. Chmilowski A., op. cit., p. 66.

through dedicated applications, where a simple slider mechanism allows users to instantly initiate coverage. This model is particularly relevant for customers who are aware of the specific risk exposure of their assets – such as video cameras, smartphones, or bicycles – and seek insurance only when the asset is actively in use and vulnerable to potential threats. As a result, protection is provided precisely when the insured asset is at risk, aligning with the growing demand for personalised and adaptive insurance solutions.

On-demand insurance can be viewed as a new business model that provides coverage only for risks that are actively present at a given moment. The key advantage of this approach is that customers can access insurance protection precisely when they need it, without the need to complete an application form or contact an insurer or intermediary. For instance, coverage is activated when a policyholder uses an asset or engages in an activity that exposes them to risk. Through a mobile application, a customer can purchase insurance instantly, whether they are riding a bicycle in public traffic, travelling abroad, or using electronic devices that are at risk of damage or theft. This model has direct cost implications, as premiums are paid only for the actual period of coverage. In other words, policyholders pay only when the insured asset is actively in use and at risk[20]. As previously mentioned, such offerings are made possible by mobile technology, particularly smartphones, which serve as the primary interface for activating and managing coverage.

In usage-based insurance, premiums are calculated based on real-time data about the insured's actual behaviour and habits. While the principle of aligning premium levels with an individual's contribution to the risk pool is not new, it is only with the advent of modern technological solutions – such as GPS tracking and the Internet of Things – that this concept has been able to be fully implemented in practice. These technologies enable insurers to collect and analyse behavioural data, allowing for a more precise risk assessment and personalised pricing models. As a result, UBI represents a shift from traditional risk classification toward dynamic, data-driven underwriting, thus improving both fairness and efficiency in premium determination.

One of the areas where UBI is increasingly used is motor insurance. The origins, development, and implementation of telematics in insurance processes date back to the 1970s, when traditional premium calculation methods – based on the statistical probability of an insured event – began to be questioned. At that time, alternative pricing models were proposed, linking insurance premiums to actual driving distances. Two premium calculation systems were introduced. The first involved incorporating the insurance premium into the fuel price, while the second proposed a collaboration between insurance companies and tyre manufacturers[21]. However, these models proved ineffective, mainly due to the failure to maintain a premium-benefit equilibrium. Additionally, including insurance costs in fuel prices favoured fuel-efficient vehicles, leading to distortions in risk-based pricing. A more effective solution emerged with the introduction of specialised meters capable of real-time monitoring of driving behaviour and tracking mileage – a concept that laid the foundation for UBI.

One of the first insurers to offer a telematics-based premium calculation system was the U.S. insurer Progressive, which launched the pilot programme 'Autograph'. Under this system, premiums were calculated based on GPS data transmitted from insured vehicles participating in the pilot

20. Lamparelli N., *On-Demand Insurance: Ultimately a Bust?*, https://www.insurancethoughtleadership.com/on--demand-insurance-ultimately-a-bust/ (Aug 14, 2024).

21. Kuryłowicz Ł., *Telematyka ubezpieczeniowa i jej wpływ na równowagę rynku ubezpieczeń komunikacyjnych*, Oficyna Wydawnicza SGH, Warszawa 2021, pp. 71–86.

project. As technology evolved, data collection devices became more efficient and cost-effective, allowing for a broader adoption of telematics-driven insurance models.

As of the mid-2010s, various pricing models have existed within usage-based insurance. In addition to traditional premium calculations, which do not incorporate telematics, the following telematics-based pricing models can be distinguished:

- Pay-Per-Mile (PPM)– These systems do not use telematics solutions, but premiums are partially or entirely based on self-reported mileage data provided by the insured.
- Pay-As-You-Drive (PAYD) or –Pay-As-You-Go (PAYG) – This model links insurance premiums directly to mileage, with distance data collected, stored, and transmitted using telematics systems.
- Pay-How-You-Drive (PHYD) – These policies utilise telematics not only to track mileage but also to assess driving behaviour. Factors such as speed, types of roads travelled, and time of day when the vehicle is in use are analysed to determine risk levels.
- Pay-As-You-Speed (PAYS) – This model implements financial penalties by reducing applicable discounts when insured drivers exceed speed limits.

The use of usage-based insurance with telematics offers potential benefits for both insurers and policyholders. Telematics-based UBI enables insurers to[22]:

- Improve risk selection, allowing for better identification of low-risk and high-risk customers.
- Conduct advanced fraud detection, enhancing the ability to identify insurance fraud and reduce fraudulent claims.
- Lower claims and operational costs, making claims processing more efficient and cost-effective.
- Enhance customer understanding, leading to higher customer satisfaction and loyalty.

From the customer's perspective, UBI offers several advantages. One of the key benefits is greater pricing transparency, as premiums are directly linked to actual driving behaviour rather than generalised risk categories. Additionally, policyholders gain personal control over their insurance costs, allowing safer drivers to benefit from lower premiums as a 'reward' for responsible driving habits. Another significant advantage is improved road safety, as UBI incentivises cautious and responsible driving by directly linking driving behaviour to premium adjustments. This model also leads to more affordable insurance premiums, which is particularly beneficial for young drivers, who typically face higher insurance costs due to their statistically greater accident risk. This last factor is particularly significant for young drivers, who often face high insurance costs due to a lack of driving experience and their classification within the highest-risk age group. At the same time, many young policyholders have lower-than-average incomes or have not yet entered the workforce, making them more sensitive to insurance pricing. UBI can help bridge this gap by offering more accessible and fair pricing models based on actual driving performance rather than broad demographic assumptions.

The growing popularity of ODI and UBI models is reflected in the sustained presence and market capitalisation of well-established insurtech firms worldwide. Although the number of global insurtech funding transactions declined slightly from 563 in 2021 to 521 in 2022, and the total capital raised dropped by 50% – a correction after the unusually high investment levels during the pandemic – insurtech companies continued to attract significant funding. By the end of 2022,

22. Accenture, *Insurance telematics: A game-changing opportunity for the industry*, 2014, http://www.accenture.com/Microsites/insights/Documents/pdfs/Accenture-Telematics-Low-Res-Version-Final.pdf.

insurtech firms had accumulated approximately $8 billion[23] for future development, and by the third quarter of 2023, this figure had already surpassed $3.4 billion[24].

3.2. Pricing and Reserving

In the field of pricing, advanced AI algorithms are increasingly used to estimate risk factors during the construction of risk models and the determination of premium rates. Through advanced analytics and machine learning algorithms, insurers can more effectively identify risks associated with insurance contracts, detect anomalies within the portfolio, and make data-driven decisions regarding portfolio management strategies. These innovations enhance pricing accuracy, improve risk assessment, and contribute to more efficient underwriting and portfolio optimisation.

The traditional approach to risk modelling begins with manual data preparation, a complex process often prone to calculation errors. During this stage, most insurers rely on basic algorithms, frequently guided by intuition and past experience rather than advanced analytical methods. For risk modelling, the commonly used approach is the generalised linear model (GLM). However, the implementation of tariff adjustments remains time-consuming and challenging, as it typically requires manual intervention and, in some cases, even hard-coded modifications to the insurer's core systems. This significantly delays the introduction of pricing changes, reducing the ability of insurers to adapt to market conditions and emerging risks.

By leveraging ML and AI, risk analysis becomes more precise and less prone to errors. ML can also support decision-making by simulating portfolio outcomes, enhancing insurers' ability to anticipate financial performance. In one of the early studies, Gan estimated the market value of a large variable annuity portfolio using ML techniques[25]. Similarly, Assa et al. applied ML methods to analyse the pricing of deposit insurance, refining implied volatility calibration to prevent mispricing caused by arbitrage[26]. Meanwhile, Grize et al. explored the application of ML algorithms in online motor insurance pricing[27], demonstrating that these techniques outperformed traditional generalised linear models. The implementation of these advanced analytical approaches has led to more accurate pricing, improved portfolio risk assessment, and greater efficiency in premium calculations, reinforcing the advantages of AI-driven actuarial methods over traditional pricing techniques.

In pricing models for new insurance contracts, machine learning algorithms commonly used include[28]:

- Classical multivariate statistical modelling techniques, such as multiple regression, GLMs, clustering methods, and classification techniques.

23. 1 billion = 1,000,000,000.
24. Gallagher Re, *Global InsurTech Report*, 2023, p. 47.
25. Vide: Gan G., 2013, *Application of data clustering and machine learning in variable annuity valuation*, 'Insurance: Mathematics and Economics', 2013 vol. 53, pp. 795–801.
26. Vide: Assa H., Mostafa P. and Abdolrahim B., *Sound deposit insurance pricing using a machine learning approach*, 'Risks', 2019 vol. 7, pp. 1–18.
27. Vide: Grize Y.-L., Fischer W. and Lützelschwab Ch., *Machine learning applications in nonlife insurance*, 'Applied Stochastic Models in Business and Industry', 2020 vol. 36, pp. 523–37.
28. Ibidem, p. 526.

- Decision trees and regression trees (CART), neural networks (NN), ensemble methods (such as random forests), and support vector machines (SVMs).
- Extreme gradient boosting (XGB) and deep learning techniques, which enhance predictive accuracy and model complexity.

These advanced tools serve a dual purpose: they enable individualised premium calculations while also allowing for dynamic risk pricing. This dynamism is evident in two key aspects. First, the speed of risk assessment is significantly enhanced, as calculations are performed instantaneously and online. Second, the scope of input data used in pricing models is broadened, incorporating both external business conditions and the internal state of the insurer's portfolio at the exact moment of risk evaluation. This capability is crucial, as it allows insurers to position their offerings effectively in a continuously evolving competitive landscape. Increasingly, insurance comparison platforms and aggregators are becoming the primary channels for reaching potential customers. On these platforms, insurers' offerings are displayed alongside competitors' products, while market players independently adjust their pricing strategies.

Artificial intelligence methods facilitate the automated monitoring of competitors' pricing changes, enabling insurers to dynamically adjust their pricing strategies in near real-time. These AI-driven adjustments take into account customer price sensitivity, ensuring that insurers remain competitive while optimising risk-based pricing. One of the most commonly used machine learning techniques in insurance pricing is clustering, which enables insurers to segment customers into homogeneous risk groups based on their risk profiles and additional characteristics. By doing so, insurers can adjust pricing levels for each group according to their behaviour and preferences. Moreover, insurers can optimise premium rates not only at the group level but also for individual customers, taking into account their **willingness to pay** as determined by expected utility, which varies across different customer segments (i.e., based on an individualised demand function). This approach allows insurers to maximise customer satisfaction while maintaining risk-adjusted profitability.

By implementing utility-based clustering in pricing, insurers can develop a more efficient and effective pricing strategy, enhancing their competitive advantage while improving overall financial performance. This approach can lead to higher customer satisfaction and loyalty, a lower incidence of adverse selection and moral hazard, and ultimately greater profitability and business growth for insurers. One possible approach to implementing this pricing strategy is through the use of a deep neural network (DNN) – an AI-driven model capable of learning from provided data and performing complex tasks. A DNN model can simultaneously handle customer clustering and pricing optimisation, leveraging a multi-task learning approach to improve efficiency and predictive accuracy. Furthermore, DNNs can enhance the quality and consistency of International Financial Reporting Standards (IFRS) 17 models, reducing uncertainty and variability in financial results. This is particularly effective when DNN-based pricing clusters align with IFRS 17 cohorts and when assumptions remain consistent across both frameworks. By ensuring coherence between pricing models and financial reporting standards, insurers can achieve greater accuracy in risk assessment, premium setting, and long-term financial stability. However, it is essential to consider the interpretability of AI-driven results, especially when applying these techniques to insurance pricing. The broader adoption of machine learning methods in property and personal insurance pricing – whether as a complement or an alternative to GLM – is often constrained by perceived opacity in their decision-making processes. To address this challenge, a strong emphasis must be placed on enhancing model interpretability. This can be achieved by ensuring transparency at each stage of the computational process, allowing insurers and regulators to trace and validate pricing decisions. In many countries, regulatory frameworks mandate a clear and explainable pricing process, requiring insurers to provide auditable and interpretable AI-driven models. Therefore, improving explainability and compliance will be crucial for the wider integration of ML in insurance pricing strategies.

Artificial intelligence is increasingly being applied in insurance reserving, capital requirement estimation, and financial health assessments of insurers. Machine learning is already being successfully used for claims reserving, incorporating a wide range of variables related to the policyholder, the insured asset, and the insurance contract itself. By enriching these models with additional claims-related data, ML-based estimations often yield more accurate results than traditional chain-ladder methods[29]. However, this does not imply a complete replacement of the chain-ladder technique: rather, ML is frequently used to enhance and refine traditional actuarial approaches, improving their overall efficiency and predictive accuracy.

One example is the Bornhuetter-Ferguson method, a variant of the chain-ladder approach, which allows actuaries to adjust calculations based on external estimates. Similarly, Bischofberger applied ML techniques to extend the chain-ladder model by incorporating an estimated risk rate, further improving the reliability of reserving calculations[30]. Examples of machine learning applications in capital requirement estimation under Solvency II and insurer insolvency prediction – for instance, using widely available financial indicators – can be found in the studies by Díaz, Segovia and Fernández as well as by Krah, Nikolić and Korn[31]. These studies illustrate how ML models can be effectively employed to assess financial stability, predict insolvency risks, and optimise capital allocation, providing actuaries and regulators with more data-driven, accurate forecasting tools.

3.3. Underwriting

Digital solutions are increasingly applied in the insurance sector at both the risk assessment (underwriting) stage and the product development stage, with the two processes becoming increasingly interconnected. Technological advancements and innovations have made these activities mutually dependent, as new data-driven approaches allow for greater integration between risk evaluation and product design. By adopting modern solutions, insurers can meet the growing expectations of customers operating in a rapidly evolving, mobile-driven environment. At the same time, by aligning their offerings with market demands, insurers aim to enhance their financial performance and strengthen their competitive position in the insurance market.

Underwriting has been enhanced with new data sources that were previously unavailable to insurers, such as the Internet of Things, public institution databases, and social networks. These

29. Baudry M. and Robert Ch.Y., *A machine learning approach for individual claims reserving in insurance*, 'Applied Stochastic Models in Business and Industry', 2019 vol. 35, pp. 1127–55.

30. Cf.: Elpidorou V. et al., *A likelihood approach to Bornhuetter–Ferguson analysis*, 'Risks', 2019 vol. 7, pp. 1–20; Bischofberger St.M., *In-sample hazard forecasting based on survival models with operational time*, 'Risks', 2020 vol. 8, p. 3; Gabrielli A., Richman R. and Wüthrich M., *Neural network embedding of the over-dispersed Poisson reserving model*, 'Scandinavian Actuarial Journal', 2020 vol. 2020, pp. 1–29.

31. Cf.: Díaz Z., Segovia M.J. and Fernández J., *Machine learning and statistical techniques. An application to the prediction of insolvency in Spanish non-life insurance companies*, 'The International Journal of Digital Accounting Research', 2005 vol. 5, pp. 1–45; Krah A.-S., Nikolić Z. and Korn R., *Machine learning in least-squares Monte Carlo proxy modeling of life insurance companies*, 'Risks', 2020 vol. 8, p. 21.

sources generate vast amounts of data, which are now leveraged to refine underwriting models and improve risk assessment accuracy. As a result, big data analytics and related technologies – such as data mining, predictive analytics, cloud computing, and Geographic Information Systems (GIS) – are increasingly being applied in insurance underwriting[32]. Big data in insurance involves processing large-scale datasets to evaluate risk, including customer classification into high-risk groups, particularly those associated with high-cost claims (HiCCs). This segment consists of a relatively small proportion of policyholders, who are responsible for a disproportionate share of insurance claims.

Big data analysis focuses on large, dynamic, and distributed datasets from multiple sources, requiring advanced AI-driven technologies for efficient processing and risk modelling. These innovations allow insurers to identify high-risk individuals more effectively, optimise underwriting decisions, and improve pricing strategies to reflect actual risk exposure more accurately. Big data analysis is inherently linked to machine learning, a subfield of AI. Unlike traditional programming, ML systems learn and improve autonomously, processing large volumes of data without the need for explicit coding. By analysing training datasets, these systems can identify patterns and generate predictions, continuously enhancing their efficiency and accuracy as more data is processed[33]. The integration of big data analytics and ML algorithms enables the detection of subtle signals, such as complex interactions and nonlinear relationships between variables, thereby improving the accuracy of risk predictions. AI also facilitates the use of diverse data types, allowing for more refined risk assessments.

Some of the most widely used ML techniques in insurance include decision trees, Bayesian inference, Markov processes, and neural networks[34]. Compared to traditional statistical models, these methods provide greater predictive accuracy, allowing insurers to make more informed underwriting decisions and enhance risk modelling capabilities. Among the simplest machine learning techniques are decision trees, particularly when used in the context of conditional control. These models are widely applied across various fields, including decision analysis, and have proven to be an effective ML tool for risk assessment and insurance premium calculation. Neural networks, on the other hand, represent one of the most advanced technologies in modern machine learning. Their effectiveness has been widely demonstrated in areas such as speech recognition and computer vision, and they are now being extensively tested for risk assessment and pricing in the insurance industry. Recognising the value of AI in underwriting, insurers are developing models that aim to replicate historical decision-making[35], enhance risk assessment[36], and predict the probability of insured events occurring. AI helps reduce information asymmetry, enabling a more precise distinction between high-risk and low-risk policyholders, thereby mitigating

32. *Ubezpieczenia cyfrowe. Możliwości, oczekiwania, wyzwania*, eds. J. Monkiewicz et al., PWN, Warszawa 2022, p. 78.
33. Kumar N., Srivastava J.D. and Bisht H., *Artificial Intelligence in the Insurance Sector*, 'Journal of the Gujarat Research Society', 2019 no. 21(7), pp. 79–91.
34. Vide: *The handbook of data mining*, ed. N. Ye, CRC Press, Boca Raton 2003.
35. Vide: Boodhun N. and Jayabalan M., *Risk Prediction in Life Insurance Industry Using Supervised Learning Algorithms*, 'Complex and Intelligent Systems', 2018 no. 4(2), pp. 145–54.
36. Vide: Dubey A. et al., *Smart Underwriting System: An Intelligent Decision Support System For Insurance Approval & Risk Assessment*, 'Proceedings of the Third International Conference for Convergence in Technology', Tamil Nadu, India 2018.

adverse selection. Additionally, AI-driven models can encourage high-risk individuals to adopt loss prevention measures or modify their behaviour, ultimately reducing fraud risk and moral hazard – a key aspect of UBI products.

Predictive analytics is increasingly used by insurers to develop models that forecast future events, generating probability-based insights that highlight increasing risk trends[37]. In underwriting, predictive analytics aids in applicant selection, filtering out cases that do not meet the risk criteria defined by the model. The insurance risk assessment process often involves setting a cut-off threshold at a low level to eliminate individuals with the highest probability of claim occurrence. The remaining risk points are then classified into premium tiers, ensuring a structured and data-driven approach to pricing and underwriting decisions[38]. Underwriting accuracy is crucial, but so is the speed of decision-making. The risk assessment process can be lengthy and labour-intensive, particularly for specialised and complex insurance products or cases where there is a high probability of data misrepresentation regarding the insured asset or individual (e.g., large corporate insurance, life insurance, or health insurance).

The digital transformation of insurance processes can streamline and accelerate risk assessment by leveraging new, tamper-resistant data sources. For example, individuals who track their physical activity can collect real-time health data and share it with insurers via wearable technologies. By integrating predictive analytics, insurers can reduce processing time and costs, which would otherwise be allocated to expensive medical examinations for potential policyholders[39]. These advancements not only enhance underwriting efficiency but also contribute to a more personalised and data-driven approach to risk evaluation.

The adaptation of digital solutions in insurance is still in its early stages, and the ultimate goal for underwriting should be the development of autonomous systems capable of making efficient, fast, and accurate decisions. These decisions should be based not only on data related to the insured asset or individual but also on the insurer's financial position and predictions regarding the future state of the existing insurance portfolio. The outcome of underwriting should go beyond a detailed risk assessment of the submitted application. It should also involve a decision on whether the risk can be accepted for coverage, taking into account the insurer's risk appetite and strategic objectives. By integrating advanced predictive models and financial forecasting, insurers can ensure that underwriting decisions are both data-driven and aligned with long-term portfolio stability.

3.4. Distribution

According to a report by the Polish Chamber of Insurance (PIU), drafted in collaboration with Accenture, one of the key aspects of the digital transformation of insurers is their effort to increase the share of digital distribution channels[40]. A crucial condition for achieving this goal is the implementation of omnichannel distribution, which ensures the full integration of all sales channels and

37. Kumar N., Srivastava J.D. and Bisht H., op. cit., p. 82.
38. Wycinka E., *Uniwersalność zastosowań modeli skoringowych*, http://media.statsoft.nazwa.pl/_old_dnn/downloads/uniwersalnosc_zastosowan_modeli_skoringowych.pdf (Dec 12, 2024).
39. Kaushik K. et al., *Machine Learning-Based Regression Framework to Predict Health Insurance Premiums*, 'International Journal of Environmental Research and Public Health', 2022 vol. 19(13), issue 7898, pp. 1–15.
40. Vide: PIU and Accenture, *Cyfryzacja Sektora Ubezpieczeń w Polsce*, Warszawa 2024, p. 76.

customer interactions within an insurance company. The role of digital transformation in this process is to facilitate this integration, enabling insurers to respond to customer needs seamlessly, regardless of the channel used to seek insurance coverage. Ultimately, the objective is to create a fully connected and responsive customer experience, ensuring that digital solutions enhance engagement, accessibility, and service efficiency.

Digital insurance distribution refers to a strategy for delivering insurance products and services through digital means, encompassing various channels such as web portals, online platforms, and mobile applications. This approach may cover the insurer's full product range or selected offerings, as well as services targeted at specific customer segments. The digitalisation of insurance distribution has been accelerated by shifts in consumer behaviour, with an increasing preference for handling transactions and services online. This trend was significantly amplified by the COVID-19 pandemic, which forced insurance companies to adapt by adopting remote work practices and expanding their IT infrastructure.

Despite these rapid changes, the market showed no significant signs of financial distress among insurers, and the sector quickly adjusted to the new reality. Beyond administrative adaptations, insurers upgraded their IT systems to facilitate online sales (distribution) and claims processing. According to Swiss Re, the coronavirus accelerated the gradual digital transformation that was already underway before the pandemic and created new business models and distribution networks that will reshape the way we operate[41]. Customers have adapted their digital behaviours in response to the pandemic's demands. For instance, in the United States, 58% of consumers reported increased online spending, 27% subscribed to at least one new digital streaming service, and 42% made more purchases via mobile devices[42].

These shifts underscore the necessity for further digital transformation in the insurance distribution process, as insurers must continue adapting to evolving consumer expectations and digital engagement trends.

3.5. Claims Management

Innovative technological solutions are being tested and implemented at every stage of the claims management process, from claim submission to assessment and payout. The primary goal of these advancements is to automate processes, reduce processing time, and lower operational costs, particularly by eliminating repetitive and time-consuming manual tasks. Digital transformation enhances claims evaluation accuracy and helps reduce insurance fraud, both by minimising human error and by employing advanced methods to detect suspicious claimant behaviour. These improvements are made possible through technologies such as the Internet of Things, wearable devices, object recognition (OR), and robotic process automation (RPA), all of which contribute to more efficient, accurate, and cost-effective claims handling.

41. Vide: Raverkar A.K., Avramakis E. and Fitzgerald C., *Why insurers need to transform digital distribution and how to do it in the digital age*, https://www.swissre.com/institute/research/topics-and-risk-dialogues/digital-business-model-and-cyber-risk/why-insurers-need-to-transform-digital-distribution.html (Jan 22, 2025)
42. Armano D., *COVID-19 will be remembered as the 'Great Accelerator' of digital transformation*, 'Forbes', 09 September 2020.

The occurrence of an insured event typically requires the policyholder to report the claim and provide documentation about the incident. Technological innovations have significantly transformed this process, with their impact visible from the moment the event occurs. As previously mentioned, telematics and the IoT – including wearable devices – collect and process data in real-time, transmitting it automatically between systems without human intervention. These technologies enable the continuous monitoring of insured assets, such as vehicles, buildings, and individuals' health, while also detecting, recording, and transmitting data on incidents directly to insurers. Moreover, these systems can alert emergency services, helping to reduce casualties and mitigate accident consequences. The ability to precisely determine the location of an accident, particularly in the case of road incidents, significantly shortens response times for rescue teams.

Beyond its invaluable role in identifying an insured event, this technology is also crucial for determining the circumstances surrounding the claim. The recorded data allows insurers to analyse how the event occurred and assess the internal and external conditions that contributed to it. This information plays a key role in fraud prevention, ensuring greater accuracy in claims assessments and helping establish the insurer's liability[43]. Claims reporting is increasingly being streamlined through the use of chatbots, voicebots, and robo-advisors, which simulate human conversation (both written and spoken), allowing users to interact with digital systems as if they were speaking to a real person[44]. As a result, these technologies enable automated claim registration 24/7, ensuring that incidents can be reported at any time without human intervention. Additionally, they facilitate the collection of essential information from the policyholder, improving both the efficiency and accuracy of claims processing, ultimately leading to faster and more effective claim resolution.

Insurers are developing various methods to streamline the claims settlement process, including mobile applications that allow policyholders to report a claim and manage subsequent stages of the process. One key innovation is the introduction of remote property inspection tools, which vary depending on the insurer. Some solutions are designed for customers, enabling them to independently document damage, while others are tailored for surveyors, who use these tools to automatically transmit collected data to the insurer. These applications also facilitate electronic document processing, eliminating the need for paper-based documentation. As a result, the claims handling time is reduced, the efficiency of claim assessments improves, and operational costs decrease, particularly in areas such as surveying expenses and site visit logistics.

The most advanced innovation in claims processing is the full automation of damage assessment and claims settlement. These solutions are increasingly being implemented for handling minor claims in motor, home, and travel insurance. The process begins with the claim submission, after which the policyholder gains access to a digital inspection tool. The claimant takes photos or records videos of the damaged property and submits the necessary documentation through the system. Based on this data, AI-driven algorithms automatically assess the extent of the damage and calculate the compensation amount. Once the claimant accepts the proposed payout, the compensation is processed immediately. This automated approach reduces paperwork and eliminates the need for human intervention in handling simple, low-value claims, significantly improving efficiency, cost-effectiveness, and customer experience.

43. Dhieb N. et al., *A Secure AI-Driven Architecture for Automated Insurance Systems: Fraud Detection and Risk Measurement*, 'IEEE Access', 2020 vol. 8, pp. 58546–58558.
44. Cranfield A. and White D., *The rise of the robo-insurer*, Ninety consulting paper, 2016, pp. 1–18.

Conclusions

The analysis presented above has led to several key conclusions regarding digital transformation and innovation in the insurance sector. The implementation of digital solutions is still in its early stages, yet AI is already being successfully applied in core areas of insurance operations, including risk assessment and pricing, actuarial science, and claims management. These technological advancements are primarily process-oriented innovations, significantly enhancing the efficiency and effectiveness of insurance technologies. As a result, digital transformation is not only reshaping traditional business models but is also paving the way for more automated, data-driven, and customer-centric solutions in the industry.

Given the observed improvements in technological efficiency, it can be inferred that the insurance sector remains in the second phase of Barras's reverse innovation cycle, focusing on process improvements. However, innovation intensity varies by segment – claims management and distribution are undergoing a faster transformation, while product innovation remains limited. Future research should explore when (and if) the sector will transition to the next stage of innovation.

This variation presents an interesting avenue for further research, which the authors plan to explore in future stages of the project. In particular, subsequent studies will aim to identify and analyse specific, measurable cases of digital transformation already implemented in the insurance sector, including quantitative data on its effects, such as improvements in operational efficiency, reduction of costs, or claims processing time. Moreover, future research will incorporate socio-cultural dimensions of technological adoption, including customer trust in AI-based decision-making systems, the role of insurance literacy, and the broader impact of digitalisation on customer relationships and market inclusion. Understanding these differences in digital adoption will be essential for assessing the long-term impact of innovation on the insurance industry and identifying emerging trends in process transformation.

Particular attention has been given to claims management, where innovative process technologies are being tested and implemented at every stage. Equally significant are the changes in insurance distribution, where digital transformation plays a key role in adapting to evolving customer preferences. The growing popularity of mobile tools enables insurers to enhance their competitive advantage by integrating cutting-edge technological solutions, improving customer engagement, operational efficiency, and service accessibility.

The rapid advancement of machine learning algorithms is creating new opportunities for risk assessment and mitigation, making their application in the insurance industry increasingly widespread. At the same time, insurers' data assets play a crucial role, serving as the foundation for the effective implementation of AI. Progress in the technological model development – with solutions becoming more sophisticated and developed in shorter timeframes – translates into both improved financial performance for insurers and higher customer satisfaction due to streamlined service processes.

A key challenge remains the enhancement of interpretability in AI-generated outcomes. In this context, it is crucial to develop solutions that allow for full traceability of the computational process at every stage. Ensuring transparency and explainability in AI-driven decision-making can contribute to greater customer trust and improve the quality of decisions made by insurers. In addition to challenges related to AI interpretability and transparency, several structural barriers continue to shape the pace and direction of technological adoption in insurance. Notably, the high costs associated with implementing AI solutions – both in terms of infrastructure and human capital – can deter smaller market participants from engaging in innovation. At the same time, the growing risk of cyberattacks poses a critical threat to insurers that rely heavily on interconnected digital systems and sensitive personal data. This highlights the need for robust cybersecurity frameworks to accompany technological transformation. Furthermore, regulatory requirements such as the General Data Protection Regulation (GDPR), Solvency II, and the Digital Operational Resilience Act (DORA) exert a significant influence on the adoption of AI in the sector. These frameworks aim to protect consumers and ensure market stability, but they also impose compliance burdens that may limit the speed of innovation. Future research should consider how regulatory, financial, and security-related constraints interact with technological capabilities to shape digital transformation trajectories in the insurance industry.

These findings highlight key directions for future research on digital transformation and innovation in the insurance sector, emphasising the importance of balancing technological advancements with transparency and regulatory compliance.

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Transformacja cyfrowa a innowacje w sektorze ubezpieczeń: procesy, technologie i wyzwania

Transformacja cyfrowa sektora ubezpieczeń usprawnia procesy oceny ryzyka, taryfikacji, dystrybucji i likwidacji szkód. Kluczowe technologie napędzające te zmiany to sztuczna inteligencja, uczenie maszynowe, big data i techniki automatyzacji. Postęp w tych obszarach przyczynia się głównie do innowacji procesowych a nie produktowych, definiowanych zgodnie z odwrotnym cyklem innowacji Barrasa,.

Autorzy wykazują, że technologie, takie jak telematyka, IoT, analityka predykcyjna i automatyzacja procesów, usprawniają operacje i poprawiają doświadczenia klientów. Jednak nadal istnieją wyzwania związane z zapewnieniem przejrzystości i interpretowalności sztucznej inteligencji. Choć cyfrowa transformacja jest na wczesnym etapie, jej dalszy rozwój będzie kształtować efektywność, konkurencyjność i uregulowania prawne w branży ubezpieczeń.

Słowa kluczowe: cyfryzacja sektora ubezpieczeń, innowacje procesowe, sztuczna inteligencja w ubezpieczeniach, odwrócony cykl innowacji Barrasa, big data w ubezpieczeniach

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