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Groenewald, Andries

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The Ethics of Personalising Risk using Big Data in the Pricing and Underwriting of Life Insurance

Andries Groenewald

Student No: 2291113

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Declaration

I declare that this research report is my own unaided work submitted for the degree of Master of Arts, Applied Ethics for Professionals, University of the Witwatersrand, Johannesburg. It has not been submitted before for any other degree or examination at any other university



Andries Groenewald

Abstract

This research report investigates whether the use of big data to personalise risk in the pricing and underwriting of life insurance undermines the delicate balance of factors that allow the industry to be morally justified. The practice of risk classification in the pricing and underwriting of life insurance can be regarded as unethical given the resemblance to discrimination. A consequentialist justification for the practice is presented. It is then investigated whether the use of new factors derived from the analysis of big data invalidates the justification. It is found that such factors can be used subject to certain conditions being met.

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1. Introducing the question

1.1 Introduction

Premiums for life insurance policies sold in the private market for life insurance (as opposed to many government insurance schemes) are set using factors such as age, gender, health and socio-economic status. This practice has left many uncomfortable and requires continuous justification in different jurisdictions and at different times. A commercial rather than ethical justification is often provided (Moultrie & Thomas, 1993). Ethical concerns may override this justification and for the industry to work in the desired way, clear rules and guidelines are required for all participants. Therefore, legislators and regulators have often stepped in and prohibited the use of certain factors (e.g., the ban on the use of gender in pricing insurance in the European Union) and even nationalised entire markets (e.g. the healthcare markets in Canada and New Zealand) where discrimination or outright exclusion of some is seen as too problematic.

This uncomfortable truce exists in many countries; practitioners and ethicists have argued for the ethics or lack thereof of the entire market using different types of arguments. In addition, over time there has been a tendency to classify risk more precisely rather than using broader groupings (Seekings & Pearch, 2020). At first glance this has ameliorated the discrimination present in the market; it does however introduce potential further ethical concerns. Factors such as the health of the individual or their income may be very predictive of the risk, and hence useful in pricing, but their use may still be problematic. Any new factor introduced may invalidate the ethical justification for the industry as the justification hinges on a delicate balance between the practical necessity of using certain factors and the morality of discriminating against people or groups of people in the provision of the product.

Such new factors include those that can be uncovered by the analysis of big data. These factors can disturb the balance of factors used in the ethical justification of the market in many unforeseen ways. The impact of the introduction of new factors and the practice of using the analysis of big data to identify such factors on the ethical justification of the industry needs to be investigated, which is the focus of this report.

This tendency to classify risk more precisely is known as the personalisation of risk. Rather than using a premium rate that reflects the cost of providing the benefit for a broad grouping (e.g. males age 40 who are smokers), a premium is used that reflects the actual risk of a specific individual.

A recent example of how the greater personalisation of risk has been found to be problematic was the use of genetic testing to reveal the risk of developing certain diseases in future. However, several countries, such as Belgium and Norway, prohibited the use of such test results in the pricing and underwriting of life and health insurance whereas others, such as the Netherlands, placed clear restrictions on when and how it can be used (Sandberg, 1995). Ultimately, the ability of many of the tests currently available to accurately predict illnesses is insufficient to justify widespread use to personalise risk rendering the debate moot. This history shows how new risk factors enabled by technology may upset the ethical justification of the industry; widespread agreement between industry, regulators and the public is required before introducing new technology into the industry and it may be found not to be acceptable.

The analysis of big data has the potential of revealing the risk of potential and existing clients more clearly to insurers. Life insurers have data spanning many years and are often part of larger financial groups and through these have access to diverse data such as transactional data from banks. New technology in the analysis of big data enable them to derive previously unknown insights about their clients.

More futuristic scenarios involving the use of big data in life insurance may include artificial intelligence revealing the precise risk of death of an individual or even the exact date of death. Although these are not conceivable in the foreseeable future, such scenarios will impact the life insurance industry and the ethical justification of the industry drastically.

1.2 The purpose of the research

The question I intend to answer is: "Does the use of big data to personalise risk in the pricing and underwriting of life insurance undermine the delicate balance of factors that allow the industry to be morally justified?"

The question is a moral question as the practices under consideration can determine access to life insurance which can be considered a basic social good (Marais, 2019). This is even more pressing in South Africa with a limited social safety net.

The question is of importance as it impacts the ethical basis underlying the life insurance industry. The market for voluntary life insurance is built on risk classification. Risk classification involves practices akin to discrimination where the elderly, males, or the sick pay more for life insurance or are denied policies. Big data is already used in the pricing and underwriting of life insurance and I will postulate that this changes the balance of many of the factors used to justify the industry. The practices therefore require investigation to determine whether the resulting industry is morally justified.

As a statistically grounded industry, insurers have vast amounts of internal data. Through their relationships with other financial institutions and insurance providers, often through common group holdings, they also have access to health, banking and short-term insurance data. This can be combined with other publicly available sources of data to form abundant datasets providing fertile ground for big data analysis. Therefore, big data is already being used by

many life insurers for a variety of purposes (Meyers & Van Hoyweghen, 2018). As with many issues regarding ethics and technology, the ethical theory about the use of big data in the pricing and underwriting of insurance lags the development of the technology.

Some uses of such analysis are merely operational in nature and on the face of it do not require further ethical consideration. Examples include analysis performed on the data to gain insight into the insurer's risk exposure in order to help them to manage their own risk and inform the setting of reserves. Big data can also be used to modernise the underwriting and pricing of insurance. It can reveal detail relevant to the risk of the applicant without relying on the applicant's honesty to disclose the information and reduce some of the problems with asymmetry of information. It can help to avoid laborious questioning and expensive medical tests. All of this can lead to a more streamlined process and lower costs of acquiring the business which can be passed on to the consumer (Burston et al., 2020).

However, where big data analysis is used to arrive at an underwriting decision or to inform the price of life insurance it has a potential impact on the prospective client. A negative underwriting outcome or a prohibitively high price can restrict access to life insurance. Even if the resulting premium rate is still affordable, the price differential needs to be justified and thus reveals to the applicant how the insurer views their risk profile. The risk may be known to the applicant, for example where the applicant suffers from a known illness or engage in risky behaviour or may be completely unknown where big data analysis reveals novel risk factors not backed by any science. Often these risk factors are not single factors but the combination of various factors making it even harder to explain. In the debate about the use of genetic testing, it was questioned whether it is ethical to require people to go for tests that may reveal hitherto unknown insights about their future mortality (Andorno & Laurie, 2004). Here similar insights are derived from big data.

The use of big data in various applications have been considered and several potential moral issues have been identified (Mittelstadt et al., 2016). These issues include concerns around bias and discrimination, concerns around the certainty of the knowledge derived from such analysis and difficulties in communicating the results to affected people. How and whether these issues apply to applications in the life insurance industry also need to be considered to understand whether the use of big data to personalise risk in the pricing and underwriting of life insurance is morally justified.

All these factors show that the use of big data and algorithms further complicate an already morally precarious industry. Its use moves the industry further away from solidarity in insurance, the principle of sharing losses, to arrive at a price personalised to the risk of the individual where everyone pay for their own losses. In doing so it may remove some of the risk classification too reminiscent of discrimination but treat people in other potentially harmful ways, such as revealing the risk of genetic predisposition to disease. Analysis is required of the interaction of the various morally relevant factors and the balance of the newly created industry. This will help insurers currently on the journey to ensure that the ensuing industry is ethical but also help consumers and regulators to demand appropriate ethical behaviour from the industry.

In light of these factors, I will argue that several of the factors that can potentially be introduced from the analysis of big data invalidate some of the premises on which the most compelling argument justifying the life insurance industry is based. A blanket moral justification of the practice of using big data in the pricing and underwriting of life insurance can therefore not be provided, but certain uses fit into the current justification of the industry whilst others do not.

1.3 Structure of the argument

In this paper I will present an ethical justification for the current practice of using risk classification in the pricing and underwriting of life insurance in section 2. This will be a consequentialist argument and I will show how it can incorporate further restrictions on which risk factors should be used as proposed by other arguments for and against the use of risk classification.

In section 3 I will explore the ethical concerns raised with the use of analyses based on big data in different applications. I will highlight key concerns which in my view may impact the ethical justification for the current practice of risk classification in the industry.

I will then explore in section 4 how the justification needs to be adjusted for practical changes brought about by the use of big data as well how the ethical concerns with the use of big data applied to the practice of underwriting and pricing in life insurance can be addressed. As a result, I argue that based on the justification of the life industry only certain uses of big data are morally justified.

1.4 Defining the concepts

For the purpose of the research the following definitions will be used for these concepts:

Life insurance

Life insurance can be defined as insurance paying on the occurrence of a life, health, disability or death event in return for a premium (Insurance Act 2017).

Pricing and underwriting

The business of any insurance company is to take on risks from individuals in return for a premium. The exact details of the risks assumed by the company will be specified in the terms

and conditions of the cover. The insurer will undertake many activities to manage its resultant portfolio of risks.

Two key activities are underwriting and pricing. Both these activities aim to shape the portfolio of risks taken on. Underwriting refers to the process of assessing the risk by considering the finances and health of the applicant and based on that decide whether insurance should be provided and if so what premium rates should be charged (Burston et al., 2020). These activities therefore have a direct impact on applicants who wish to acquire such insurance as it will determine whether they can get the desired cover and what the specific terms and the price of the cover will be. This can be contrasted to other activities such as reserving which impacts the insurer but has no direct impact on any customer (CRO Forum, 2012). It is therefore much more important to ensure that practices used in underwriting and pricing, and indeed the activities themselves, are ethical.

Personalisation of risk

Various strategies can be followed when pricing insurance. One approach would be to charge the same premium for everyone. This is often the case in compulsory social insurance schemes run by governments. A more common approach for commercial insurance is to assess the risk and to base the premium on the risk of the individual. This is generally done by considering broad groupings using factors such as age and gender (Marais, 2019). Personalisation of risk refers to the trend towards using more granular groupings reflecting the risk of the particular individual rather than a broad grouping (Seekings & Pearch, 2020).

Big data

Big data is a topic much written about in the last number of years. This is a term that is ubiquitous, yet not clearly defined and used differently in different contexts. For the purposes

of this research, it is defined as the analysis of big datasets combining large volumes of data from diverse sources using statistical techniques. These include traditional statistical techniques to identify relationships, such as regression analysis, but also more advanced techniques such a machine learning, neural networks and random forests (Burston et al., 2020). The more advanced techniques often involve algorithms interrogating the data and producing relationships that are often not easily understood by humans (Mayer-Schonberger & Cukier, 2017). The results of such analysis are operationalised through algorithms that can make decisions (Mittelstadt et al., 2016). In the case of the research these decisions will relate to the pricing and underwriting of insurance. These algorithms are often dynamic and can teach themselves over time to make better decisions by feeding back information about the success of their prior decisions.

2. The justification of the life insurance industry

Life insurance is an established product and, as explained already, a morally troubled one given many practices akin to discrimination. Although big data introduces many new possibilities for the industry, the changes resulting from the use of big data are more subtle than for many other applications as the life insurance industry has traditionally been collecting, analysing and using data to inform risk classification. To investigate the ethical use of big data in the pricing and underwriting of life insurance, it is firstly necessary to understand the ethical justification for the industry in its current form. The changes effected to the industry by introducing big data can then be assessed be referring to the above justification, to verify that the resultant industry is still ethically justified. As big data involves various practices and types of factors, these will have to be assessed separately.

Many arguments have been presented to justify the ethics of underwriting and pricing in life insurance using different types of arguments. Given that the life insurance industry is often heavily regulated and forms an integral part of the social security system of many countries, the practical and ethical constraints imposed by law, regulation, public sentiment and business considerations also need to be taken into account.

The main approaches followed in assessing the ethics of pricing and underwriting in life insurance are efficiency arguments relying on consequentialist theory, arguments based on discrimination and arguments based on social justice and fairness. I will develop the consequentialist approach in more detail in section 2.1 as it will be shown that it can incorporate practical constraints with other legal and ethical constraints, even ones rooted in other ethical theories. This will provide a single approach to measure the use of big data against.

2.1 The consequentialist justification for the life insurance industry

Several arguments aimed at defending the use of risk classification in the pricing and underwriting of life insurance rely on the mechanics of the private, voluntary market for life insurance (CRO Forum, 2012; Heath, 2014). These arguments show how failure to allow for all relevant information in the pricing and underwriting of life insurance makes the market less efficient; sometimes it can even lead to a complete breakdown of the market. It should be noted that information used in this report pertains merely to information about the risk being assessed in underwriting and not information about prices, quantities, volumes and suppliers generally used in the theory on efficient markets. Although these are efficiency arguments rather than ethical arguments, the ethical basis for such arguments can be derived from the consequentialist approach to ethics. If it is assumed that life insurance provides a benefit for the insured, his or her beneficiaries and wider society, then measures aimed at aiding the market are morally permissible so long as the benefit outweighs the harm imposed on some in the form of higher premiums or exclusion from the market. These arguments therefore show that risk classification makes the market for life insurance more efficient and hence larger. I will develop the consequentialist argument in this section and in the following section show how some of the constraints motivated by other types of arguments can be incorporated into this argument. I find the consequentialist argument presented to be a powerful moral justification for the industry, in part because of its ability to incorporate ethical considerations prioritised by other approaches.

Definition of consequentialism

Consequentialist moral theories are a wide range of theories judging the rightness of something by assessing the eventual outcome or consequences. Such theories therefore require a theory of value to compare different outcomes. The means for achieving the end state derives its moral

goodness from the value of the end state. The end state is used in assessment and the means for achieving the end state carry no moral weight on its own (Talbott, 2013). The exposition of the argument will show how such a theory can be applied to the practice of risk classification in the underwriting and pricing of life insurance.

A basic consequentialist theory is hedonistic act utilitarianism (Driver, 2005). Utilitarianism is a maximizing theory; it judges the moral rightness of an act by assessing whether its consequences maximise the overall good. The measure of value used is hedonism: the pleasure or pain derived by people from the consequences of the act. Therefore, in order to apply the theory, a moral agent must determine for every act the pleasure and pain resulting from that action for all people affected and calculate the net amount of pleasure. The action yielding the most pleasure is the morally right action (Shafer-Landau, 2012).

Indirect consequentialism

Other versions of consequentialism adjust some of these features. Rather than using the theory to judge individual acts it can be used to assess rules; for rule utilitarianism, for example, the right act would be the one that follows a rule that maximises utility (Driver, 2005). Consequentialism can also be used to assess institutions and social practices. When the level of assessment is elevated from acts to rules, institutions or social practices it can be described as indirect consequentialism (Talbott, 2013). As already mentioned, the version used to justify the insurance industry will not be applied to individual *acts*, but rather the *practice* of risk classification in underwriting and pricing of life insurance and eventually to the use of big data as part of this practice.

Value measure used

The theory of value underlying the consequentialist calculation needs to be specified. Hedonism view pleasure as the ultimate source of value and anything that contributes to pleasure as good. However, this version is often criticised for being too superficial and not allowing for a wide range of other ideals (Brandt, 1959). In addition, it is difficult to compare the pleasure experienced by different people and even though a single measure of value is used, namely pleasure, it can be shown to have multiple dimensions, such as intensity and duration (Driver, 2005).

To address this concern, pleasure can be substituted with the satisfaction of preferences as the measure of value (Goodin, 1991). Neither of these measures are appropriate to justify life insurance as life insurance involves the purchase of a future promise and therefore do not give immediate pleasure or satisfy any immediate preferences.

Another version known as welfare utilitarianism uses welfare as a measure of value (Goodin, 1991). Welfare is a broad measure of the resources available to people to pursue their preferences. Although, this is not specified as an economic measure in a market economy wealth would be one important component of the resources required to satisfy preferences. This also links with welfare economics where newer versions make social welfare judgments on the basis of monetary cost-benefit analyses, or systems where the gainers compensate the losers in some way (Fleurbaey, 2021). There is also a sub-field of welfare economics which uses measures of national income, such as the gross domestic product (GDP), as the measure of value. The consequentialist measure of value adopted from here on in this report will therefore be economic welfare, which in many instances equates to GDP. This is the appropriate measure to use when analysing insurance as it captures the wide-ranging benefits of life insurance for the individual and the direct impact of life insurance on the economy through the benefits paid.

Applying the value measure to life insurance

As a first step in applying the consequentialist argument to the practice of risk classification in the pricing and underwriting of life insurance, I will show how life insurance contribute to economic welfare, the value measure that will be applied. The product itself is of limited value but is instrumental to creating economic welfare through three mechanisms: the impact it has on the behaviour of the individual who purchase it, the economic benefit to those who receive pay-outs from life insurance policies and the contribution of the life insurance industry to the economy through the long-term savings it enables.

- Impact of life insurance on the individual who purchase it:

  Like most products, life insurance does not have value in itself, but derives value from providing a benefit to those who acquire it. This benefit needs to be explained. Despite rapid development in many areas, all humans are still subject to death and have limited control over the timing and circumstances of death. The constant threat of death is always present. The untimely death of the breadwinner of a family can plunge a family into extreme poverty. This uncertainty may result in people leading debilitatingly risk-averse lifestyles.

  Life insurance is a means that enable individuals to convert the uncertainty of death to a certain cost by pooling the risk with other individuals. This is known as chance solidarity (Lehtonen & Liukko, 2011). Through this mechanism, insurance gives people the ability to live productive lives and embark on long-term projects such as raising a family, studying and starting business ventures without worrying about premature death. Should something happen to them, the insurance will pay an amount to enable these long-term projects to continue to some extent.

  These long-term projects and increased economic activity will result in more welfare for the individual and for the wider economy. It therefore contributes to economic

welfare, the measure of value used in the argument. Life insurance as a product therefore derives its value as it is instrumental to provide the benefits for individuals and society described in this section.

Two further concepts, although not rooted in consequentialist theory, can help to clarify the benefit of insurance for the individual. The first is the concept of primary social goods as used by Rawls (Wenar, 2017). Sandberg (1995) applies this concept to life insurance and in the analysis distinguishes between three types of goods: primary social goods, non-primary social goods and mere commodities. Primary goods are "goods that everyone needs for leading a life under decent physical conditions." (Sandberg, 1995). Non-primary social goods fall between primary social goods and commodities – they can help to contribute to a decent life but are not essential. Whether insurance is classified as a primary social good or a non-primary social good therefore depends on the social security benefits provided in a country – where there is none or very little, insurance is a primary social good. The limited social safety net in South Africa will invoke the classification (Marais, 2019). The justification of the industry still holds even when life insurance is a non-primary social good but may be weaker as the benefits of insurance are provided elsewhere.

The description of life insurance as a means enabling individuals to lead productive lives also links to the capability approach in philosophy. The focus in this approach moves away from basic goods as described by Rawls, to the effects such products have on humans (Sen, 1979). This approach focuses on the concepts of *functionings*, which are things humans can do or achieve, and *capabilities* which refers to their ability to realise the functionings in practice. Functionings refer to a wide range of states and activities that can contribute to human well-being such as getting married or travelling. *Conversion factors* are things that enable humans to realise capabilities; in the language

of capability theory, to convert them into functionings (Robeyns & Byskov, 2020). If this framework is used to explicate the benefit of life insurance, life insurance would be a conversion factor enabling humans to achieve the functioning of a productive economic life, which would contribute to their well-being.

These two concepts, although not based in consequentialist theory, help to illustrate how life insurance, through its impact on behaviour, contributes to economic welfare. Rawlsian theory or the capability approach will not be used further in this report.

These benefits can also be achieved by other means such as the provision of social security benefits by a country or having sufficient wealth, so life insurance is not the only means for achieving this benefit. The benefit for individuals of having life insurance therefore depends on their individual circumstances and the social safety net in their country of residence. In countries with a limited social safety net the requirement to leave something behind for your family will provide more benefit than in countries with more extensive benefits. This overall benefit will also be larger for the economic welfare of the country.

In addition, there will be a diminishing marginal utility of additional life cover with no further utility being obtained from increases in life cover above a certain limit (Nyman, 2001). The limit may again vary between individuals depending on their circumstances, such as other sources of wealth. Swiss Re estimates the protection gap, the difference between how much insurance people need and what they currently have, as $25 trillion in 2018 (Swiss Re Institute, 2018). It is therefore not likely that increasing the market for insurance will result in no increase in utility for most people; given the protection gap the aggregated utility of all individuals should increase.

- The economic benefit of life insurance for those who receive pay-outs:

Another way in which life insurance provides a benefit to society is through its impact on the beneficiaries – the recipients of the benefit when the insured life dies. According to statistics compiled by the Association for Savings and Investments in South Africa (ASISA) life insurers paid out claims to the amount of R522.7 billion to beneficiaries and policyholder in 2020 (ASISA, 2021). The injection of this money into the economy directly benefits the economy, but it also indirectly benefits the economy as fewer people are at risk of losing everything after the death of a breadwinner and requiring social benefits from the government.

- Contribution of the life insurance industry through the long-term savings it enables:

  The benefit of life insurance is also evident from the huge demand globally for life insurance. In 2019 the total global premium for life insurance was $ 2 916 billion according to a study conducted by the global reinsurer Swiss Re (Swiss Re Institute, 2020). The life insurance industry contributes to economic growth, through the benefits of long-term savings and the amounts paid out to beneficiaries (Cummins et al., 2018).

The consequentialist argument justifying the practice of risk classification in the pricing and underwriting of life insurance

The argument is developed as follows: firstly, it has been shown how life insurance contributes to economic welfare; from this it follows that the private life insurance industry is good as it provides this product that contributes to economic welfare, the chosen measure of value. The next premise of the argument is that because of adverse selection, the private life insurance industry will not be possible or much less efficient and hence smaller if risk classification in the pricing and underwriting of insurance is not permitted. The end state where risk classification is allowed will therefore be a larger, more efficient industry providing more overall good and applying consequentialist reasoning something is morally permissible if it

brings about the most value compared to alternative states of affairs (Sinnott-Armstrong, 2019). Therefore, risk classification in the pricing and underwriting of life insurance is morally permissible.

Adverse selection in insurance requires further explanation. There is an asymmetry of information between an applicant and the insurer as the applicant knows more about factors relevant to their risk of death than the insurer. If the insurer does not learn all the information relevant to the pricing of the insurance and use such information, any rational applicant would buy the insurance when their risk is higher than what the premium suggest. This is the problem of adverse selection (Meyers & Van Hoyweghen, 2018). Given that the experience of the scheme will now be worse than what was priced for, the insurance scheme will incur losses.

Adverse selection can lead to the complete breakdown of an insurance market in extreme cases. As an example, consider someone who is terminally ill with less than a year to live, buying a life policy with a large sum assured. If the insurer does not allow for the illness, the premiums received will only be a fraction of the amount paid out on imminent death. The overall market may break down because of the feedback loop between more individuals for whom the premium does not reflect their risk buying the insurance, the experience being worse than priced for and increases in price.

However, the effects of adverse selection are moderated in practice by the lack of alternatives for the low-risk individuals and only a rudimentary understanding by the potential customers of life insurance of how the degree of risk should impact pricing (Heath, 2014). Low risk individuals may therefore continue to purchase insurance despite it being more expensive than their risk, either because they are not aware of this or because there are no alternatives to insurance available. The argument that adverse selection will harm the industry is valid for obvious risk factors such as old-age or having a serious disease like cancer, which are well

understood by most individuals, but less well for more opaque risk factors. Adverse selection can therefore not be automatically extended to justify very granular risk classification, as this level of knowledge is unlikely to be available to the public and hence cannot be used to select against the insurance company.

It also works well in well-developed markets where many alternatives are available such as the market for policies providing high cover amounts; in such markets people will try to fill niche needs with insurance and many alternatives will be available. This can be juxtaposed to the market for small funeral insurance policies in a country with a limited social safety net. In such cases there will be much more scope to apply broad risk rating without being exposed to adverse selection as there is a clear need for such products and few alternatives available.

The last step in the argument is to compare the industry where risk classification is performed to one where it is not. It has been argued that risk classification in the pricing and underwriting of life insurance prevents adverse selection. Given the negative impacts of adverse selection to the industry, an industry where risk classification is applied will therefore be a larger, more efficient industry. Given the economic welfare benefits of life insurance, such an industry will maximise economic welfare. The practice of risk classification in the pricing and underwriting of life insurance is therefore morally permissible.

2.2 Incorporating prohibitions against discrimination into the justification

In many countries, laws guarantee citizens basic human rights. Linked to this are often prohibitions against discrimination. Human rights theory is not easily compatible with consequentialism as consequentialist theories have no regard for the steps taken to arrive at the end state. These steps can therefore disregard the rights of individuals (Talbott, 2013). Risk classification is in essence a method of discriminating against people based on factors identified to influence risk. While there are various methods attempting to incorporate rights into

consequentialist frameworks, one of which is the capability approach described in section 2.1 (Robeyns & Byskov, 2020), these will not be my focus. In this section I will instead consider how the justification for the life industry that has been presented can be extended to incorporate anti-discrimination laws.

Several authors (e.g. Heath, 2014; O'Neill, 1997) have grappled with the morality of the discrimination in the pricing and underwriting of insurance. Parallels are drawn to other areas where discrimination based on factors such as age, gender or medical status is not allowed (Liukko, 2010).

Although no standard definition of discrimination exists, the concept often includes the requirement that the factor used to determine differential treatment must be "socially salient and structure interactions in important social contexts" (Altman, 2020). There are therefore two elements to discrimination, the factor forming the basis of the discrimination and the impact of the differential treatment. For discrimination to be immoral, the factor used to differentiate must be something that already is prominent in society and negatively affect social interactions and the allocation of benefits. Factors such as race and gender being prime examples. Differential treatment based on a factor such as eye colour, which is not a prominent feature in most societies would not fit the definition. However, over time as more and more people base treatment on a factor it could become prevalent in society and hence a source of discrimination.

The differential treatment also needs to be harmful to the individual, as differential treatment can often be targeted at rectifying existing social inequities. Given that discrimination is dependent on the social context, differential treatment based on certain factors may be regarded as discrimination in certain countries as a result of their history and structure of society and not in others. As an example, in a country like South Africa with large income-inequality, differential treatment based on this factor is problematic as the level of income often the result

of historical factors outside the control of the individual. In wealthier, more egalitarian societies this will be less problematic.

It has already been shown that life insurance is often beneficial to individuals and contribute to economic welfare. Denying individuals cover or charging them unaffordable rates for something that contributes to their well-being is therefore harmful to the individual. If the differential treatment is based on a factor such as age, gender or health, which already are significant determinants of benefit allocation in society, this could be classified as discrimination. Other risk factors, such as smoking status is less problematic as the habit of smoking do not generally influence allocation of resources in society.

Discrimination is closely linked to fairness. In general fairness refer to impartial treatment. When applied to access to goods that are beneficial, or primary social goods, one definition would be equal access for everyone. Risk classification in pricing of underwriting of insurance limits the access to insurance based on certain inherent characteristics and could therefore be regarded as unfair.

The concept of fairness is even more nuanced in insurance. The dimensions of fairness of need and fairness of access can also be considered: namely that those who need insurance can obtain it and have access to it. Using risk classification can clearly frustrate these fairness goals. A further dimension is its application over time; life insurance is generally a long-term commitment and fairness needs to be considered over the term of the contract (Minty, 2021).

It is also not universally agreed that differential treatment in insurance is unfair. Proponents of risk classification usually invoke the concept of actuarial fairness to justify differential premiums (Moultrie & Thomas, 1993). This is a technical concept referring to policyholders paying a premium representative of their risk. This practice may result in very unequal treatment and can be understood to contradict the ordinary definition of fairness. Meyers and

Van Hoyweghen show that the concept of actuarial fairness has been enacted in different ways and until recently actuarial fairness was merely a technical concept and not an ethical claim (Meyers & Van Hoyweghen, 2018).

Applying the ordinary definition of fairness, charging a higher premium for someone who is sick is unfair; applying actuarial fairness this is fair as they pay the same for the risk they bring to the scheme and not charging more for someone with more risk would be unfair. Actuarial fairness places the emphasis on the fact that people pay equally what they can expect to receive from an insurance scheme rather than equal access at the same price irrespective of the expected benefit.

Complicating matters further, actuarial fairness is not easy to prove by observing the actual experience of a small population. Often insured lives classified as high risk, and paying much higher premiums, may survive over a given period while those classified as low risk may die. Insurance relies on the mechanism of the pooling of risk to obtain predictable experience for a large population of similar lives; the experience of individuals remains uncertain which is why they purchase insurance. Heath explains this apparent breakdown of actuarial fairness as follows: given that it is unknown when the insured event will occur, equal treatment *ex post* is impossible and hence equality *ex ante* should be strived for. This requires the equalisation of payment between people bringing different levels of risk to the scheme (Heath, 2014).

In areas other than insurance, discrimination may also be permissible. By drawing parallels between such practices and risk classification in pricing and underwriting in insurance, these arguments can also be used to justify discrimination in insurance. Heath cites as an example the *City of Los Angeles Department of Water and Power v. Manhunt* case before United States Supreme Court about the practice of charging higher premium rates to women belonging to an employer pension scheme. The law in the United States distinguishes between permissible and

impermissible discrimination – discrimination is permissible if there is a business necessity for treating employees differently. An example would be requiring employees to pass a weight-lifting test for certain jobs in manufacturing. However, excluding women because they are less likely to pass such a test would be impermissible. The ruling found the practice of the pension scheme to be impermissible as the relevant characteristic permissible to discriminate by is how long people live. Heath explained how this judgment is flawed as there is no way to determine this characteristic until it happens and hence statistical inference with other factors are required (Heath, 2014).

Other authors feel that the moral justification of discrimination depends on the actual factors used to differentiate risk. Marais uses Scanlon's contractualism to show that while the use of age, gender and smoking status may be morally justified when underwriting life insurance, socio-economic status is problematic for use in the South African context (Marais, 2019).

Legislation differs in different countries with restrictions imposed on the use of certain factors such as race or gender in various jurisdictions. In many countries such discrimination is prohibited by law and will not be allowed in any kind of market. Interestingly, even countries prohibiting discrimination by certain protected characteristics scope insurance out of such anti-discrimination laws. As an example: South Africa gives life insurers fairly wide scope to differentiate premiums between different groups as long as the distinction is "actuarially justified" (Insurance Act 2017). It is not defined how this justification must be measured.

It is worth reiterating that any factor used to classify risk, and hence inform the premium and eligibility of the applicant, must be an acceptable basis for discrimination in the relevant jurisdiction. As an example, the Court of Justice of the European Union ruled in March 2011 that the use of gender as a rating factor in insurance is in violation of the principle of equality (Lehtonen & Liukko, 2011). The laws of the country, prevailing practice and public sentiment

are all important in determining whether a factor may be used. These restrictions generally deal with factors inherent to humans such as gender, race, age and health status.

Such constraints on which factors may be used in the risk classification underlying pricing and underwriting of life insurance can be shown to be compatible with the consequentialist argument presented.

The consequentialist justification for risk classification in the pricing and underwriting of life insurance may yield different results in different countries and at different points in time as the society in which such an industry operates would need to be taken into account. The social context impacts the consequentialist calculation in at least two ways that would place restrictions on the discrimination that would be acceptable in the industry.

Firstly, any industry and its constituent companies need to adhere to the laws and regulations of the jurisdictions in which it operates. The life insurance industry in most parts of the world is a heavily regulated industry with strict licensing requirements. Any company not adhering to laws and regulations would face penalties and could have its license revoked. In countries where there are laws against discrimination based on certain factors it will therefore yield the best consequences for companies to follow such laws. Secondly, the impact on the company from enacting an unpopular decision and the consequential damage to reputation should enter the consequentialist calculation.

2.3 Incorporating social justice considerations

Social justice is an important feature in many countries and societies. There is general agreement that a society should look after the less fortunate. This is enacted through systems of progressive taxation and universal social benefits. Risk classification in the pricing and underwriting of life insurance can be viewed as contrary to these ideals as it reduces the sharing

of risk. In this section I will show how the consequentialist framework can be extended to incorporate elements of social justice.

Many arguments against risk classification arise from the view that insurance should play a role in ensuring social justice and redistribute resources from the fortunate to the less fortunate. It has already been argued that life insurance is beneficial for both individuals and society. In addition, in modern society life insurance is often a requirement to obtain home loans and other forms of credit. Excluding people from these benefits based on their ill health or other misfortune loosens social justice.

To illustrate this, Rawls's second principle of justice as fairness can be considered. He postulates that social and economic inequalities should be to the greatest benefit of the least advantaged members of society (Rawls, 1971).The higher premiums or exclusion from life insurance based on current practices will in many instances be detrimental for the sick or the elderly or in general terms those suffering from the misfortune of a higher risk of impending death. The consequentialist argument presented justified these practices; it therefore needs to be considered whether social justice is at all compatible with the argument.

The debate for and against risk classification in insurance is often presented by highlighting the tension between the two insurance concepts of mutuality and solidarity (Moultrie & Thomas, 1993). Solidarity is the basis of most state insurance schemes where the premium rate paid is set by reference to a factor not related to risk, such as a flat amount per person or a premium rate based on income, with no regard to the risk of each insured. As the name suggests, this is based on the concept of social solidarity, where society shares the burden of misfortune. Mutuality is a different term for risk classification in the pricing and underwriting of life insurance as already explained; each insured pays a premium representing the risk they bring to the scheme (Wilkie, 1997). This avoids adverse selection. Mutuality is also known as equity

in pricing or, as discussed earlier, actuarial fairness, but the concept deviates from the general conception of social justice and invokes a kind of fairness for only those already in the insurance pool and not wider society (Landes, 2015).

O'Neill argues that because life insurance ultimately aims to satisfy more fundamental needs, such as providing for a family, than for example car insurance, it requires ethical values to receive more weight than pure commercial considerations. One such ethical value that should be aimed for is solidarity (O'Neill, 1997).

In a paper exploring the concepts of mutuality and solidarity in insurance, Wilkie elaborates this line of thinking by highlighting that the ideal of solidarity is a universal measure and cannot apply to subset of a population such as an insurance pool. Universality also implies some level of compulsion; any scheme that aims to enact social solidarity cannot rely on the benevolence of the fortunate to help the unfortunate. Hence social solidarity is often enacted in national insurance schemes or social security benefits provided by the state, but is not a sensible goal for a voluntary insurance scheme (Wilkie, 1997).

Even if it is agreed that the purpose of voluntary insurance schemes is not to enact solidarity in society, some argue that solidarity can also be regarded as a moral ideal within a voluntary insurance scheme. Whilst protecting the integrity of the scheme from adverse selection from those outside the scheme wishing to enter the scheme, the ideal of solidarity can still be enacted in the scheme. Lehtonen and Liukko argue that solidarity is inherent to insurance as the aim of insurance is to equalise the uncertainty from an event such as death between the members of the insurance scheme. As risk is personalised either through risk rating or using individual factors such as the results of genetic testing, the solidarity in the scheme is reduced even further. This is presented as a critique of risk classification (Lehtonen & Liukko, 2011).

The debate around how to ensure that life insurance fits in with the social justice objectives of a country and society over time is relevant. The consequentialist argument presented in section 2.1 showed that because of the importance of insurance for individuals and the economic welfare it creates individuals and society, risk rating rather than solidarity is indeed morally justified. However, factors external to insurance and specific to the country in question should also be considered. The consequentialist theory therefore can in limited circumstances be consistent with allowances for solidarity.

As an example, in South Africa a limited social safety net is available. Many cultures in South Africa also place a high value on a decent funeral. In many markets funeral cover is available in the market to meet this need; these are low value policies with little or no risk rating making it pervasive in the market. The consequentialist argument presented can be extended to allow for the provision of a minimum level of cover without applying risk rating. The argument presented maximised economic welfare and life insurance was a means to achieve this. The life insurance industry is merely a conduit for providing the benefits. In a situation where the benefits of life insurance, elaborated in section 2.1 cannot be obtained outside of the private market for life insurance it will therefore fit in with the argument to adjust the industry to provide such benefit. One such example would be through the provision of small, non-underwritten policies.

The first reason for restricting underwriting for such policies is merely a function of the size of the policies: irrespective of the benefit of underwriting, the cost of any medical tests or even extensive medical questionnaires is unlikely to be recouped from such small policies. It is therefore more efficient to exclude such factors.

Given the lack of a social safety net and state benefits to cover funeral expenses, limited alternatives are available. Lower income groups also generally do not have sufficient wealth

and savings to fund these expenses from. Therefore, limited alternatives exist, and adverse selection pose no material threat in such circumstances.

In this section an argument justifying the practice of risk classification in the pricing and underwriting of life insurance was presented. It is a consequentialist argument, and this approach was chosen as it was shown that many other ethical constraints on risk classification can be incorporated into this framework. This framework will be applied in the following section to determine how the justification deals with the changes to practices introduced when using big data to personalise risk.

3. The ethical issues with the use of big data

The ethics of the use of big data is still a nascent field. Floridi and Taddeo describes the field of data ethics as "a new branch of ethics that studies and evaluates moral problems related to data, algorithms and corresponding practices in order to formulate and support morally good solutions" (Floridi & Taddeo, 2016). Several themes that are relevant to the topic can be identified from the literature on the ethics of big data and the guidelines issued by various industry associations. A coherent ethical framework for scrutinising these issues could not be identified from the literature; however, many of the issues are rooted in rights or legal theory. The following three themes will be discussed in more detail in the section, namely issues related to bias and discrimination, epistemic issues and issues related to communication. How these issues impact the life insurance industry and the ethical justification for the industry will be explored in the next section. As an example, the fact that the analysis of big data could result in discrimination is often raised as an ethical concern with such analysis; the risk classification of life insurance already allow discrimination to a certain extent. However, it will have to be determined whether discrimination enabled by big data is different in such a way as to alter the justification for the practice.

However, before discussing the identified themes, a few ethical concerns with the use of big data will be raised that will not be further considered. The invasion of privacy is often raised as a potential peril of big data analysis (Mittelstadt & Floridi, 2015). Through the analysis of data and the combination of diverse datasets, personal information may be derived even when the personal information is not contained in the original data. This may include data of a sensitive nature such as health status, religion, and political affiliation. Even though derived, this information needs to be treated as sensitive and more onerous rules may have to be adhered to when processing such information. This is less of a problem for life insurance, where it is current practice to process sensitive personal information such as health information. However,

through the analysis of big data this information can now be obtained without directly asking for it from the applicant. Hence insurers will have to take due care to obtain the necessary consent in the process.

A further issue raised with the analysis of big data specifically relates to providing consent for what any data may be used for (Mittelstadt & Floridi, 2015). This becomes problematic where data scientists use existing datasets for novel purposes that was not originally intended. This may be pronounced for the life insurance industry where data spanning decades are available. The life insurance industry is built around the processing of personal information and has been doing this for many years; it is therefore assumed that the additional privacy and consent considerations arising from the use of big data can be easily accommodated by the industry. These concerns will therefore not be discussed in more detail here.

3.1 Bias and discrimination

There are several potential sources and types of bias resulting from the analysis of big data; when this bias informs algorithms or other decision-making procedures it may lead to discrimination (Rovatsos et al., 2019). However, often the differential treatment may be much more nuanced than egregious discrimination. The fairness of differential treatment in the relevant context needs to be assessed. It was already illustrated that it can be argued that differential treatment in the pricing of underwriting of life insurance can be fair (Moultrie & Thomas, 1993).

Although bias is present in many activities, any bias built into algorithms may quickly scale to reach worrying proportions (Rovatsos et al., 2019). The bias can result from any step in the process of the analysis of big data and implementing this into a decision-making procedure. One source of potential bias is the data used in the analysis. Where the past outcomes described by the data, such as decisions on who is granted insurance, are biased, the analysis will replicate

this bias in the algorithms produced. The dataset may also not adequately represent certain segments of the population and therefore produce an algorithm that is less effective at making decisions about that segment, or even outright exclude them from the benefits of life insurance. This is likely to occur where certain groups were historically excluded, and past data is used or where there is low penetration of technology or services into certain groups (Barocas, 2014).

Bias can also enter algorithms through the people involved in the big data analysis (Society of Actuaries, 2019). Throughout the development process there are multiple decisions; examples include decisions about which data to include, how to order data, types of models, model structures and parameters. These decisions may be taken to deliberately introduce bias, but bias is more likely to be the unintended consequence of lack of diversity in the team developing a model (Burston et al., 2020). Choices on how the algorithms are implemented and used can also introduce bias in the process, for example where algorithms are only used for applicants using online channels. Where machine learning or other reinforcing algorithms are used, the bias may enter the decision making over time without any human intervention.

Most of the analysis of bias and unfair treatment resulting from the use of big data focus on unintended bias against the members of a protected class.

However, further types of bias also need to be considered. Big data can be used to overtly discriminate against certain groups. The big data analysis can reveal the characteristics, such as race, that may not be otherwise available to the decision-makers given existing laws about the collection and use of such information (Barocas, 2014). This will not be considered further as this use is not ethical due to factors that are not specific to big data and is, in many jurisdictions, unlawful.

A large body of work exist about the epistemic and moral problems of basing judgment of individuals by reference to a group. These groups can be defined based on any characteristic

in the data; while it may not be a protected characteristic, individual behaviour is still predicted based on membership of a group. The two ethical concern raised are as follows. Firstly, individuals are often not aware of which groups they are allocated to and hence cannot challenge the conclusion. Secondly, the knowledge derived from big data is at the population level, nothing is known about a particular individual. As an example, when an insurance premium is set for this individual based on membership to a group it must be paid by this individual. There is therefore a real effect on the individual (Mittelstadt et al., 2016).

A further category of bias is the danger of overly precise inferences (Barocas, 2014). Although this is presented as a negative in the literature, this could in fact lessen the concerns of discrimination as inferences are now more individual. However, Barocas mentions the example of insurance where more precise risk classification reduces the solidarity in insurance and according to him the purpose of insurance (Barocas, 2014). In the context of the pricing and underwriting of life insurance this is the personalisation of risk.

Various methods are suggested to prevent bias. These range from composition of diverse teams to statistical methods to test whether any bias is present in the data (Rovatsos et al., 2019). The ability to do this is often frustrated by not having data on the protected characteristic available, but it can be shown that it may even be problematic to exclude the characteristic even when such data is available. Even when excluding the protected characteristic and any proxies for it, the actual distribution of the data by the protected characteristic still causes the results to be biased. Further manipulation is required to create truly unbiased results (Lindholm et al., 2020).

3.2 Epistemic concerns

A second theme relates to epistemic issues. Where the results of any analysis inform actions affecting individuals, the bar for conviction in the results should undoubtedly be very high. This bar is often not met by analysis of big data. A key concern in this regard is that the methods

used in big data analysis are effective at identifying correlations in the data. However, this seldom proves any causal relationship and is often merely prompts further research (Mittelstadt et al., 2016). This leads some to hail analysis based on big data as the "end of theory" making scientific investigation obsolete (Anderson, 2008). The absence of theory in such analysis can be viewed as a benefit as this enables new relationships to be explored free of the constraints of *a priori* theories (Grindrod, 2016). However, once the analysis informs action this may not be appropriate and certainty about the causal relationship rather than correlation observed in the data may be required. This will have to be considered when using these correlations in the pricing and underwriting of life insurance.

A further concern is often raised with the inscrutable nature of algorithms (Mittelstadt et al., 2016). This is often a function of the methodology; machine learning or other reinforcement techniques discover relationships independent of any human oversight. Complex statistical techniques are not explainable in terms of simple relationships. Often the outcome relies on values and relationships between multiple factors. It is therefore difficult for humans, from lay person to expert, to interrogate the results and hence trust the outcome.

The importance of accountability and oversight is highlighted by many (Burston et al., 2020; Royal Statistical Society & Instititute and Faculty of Actuaries, 2019). The actions required by companies to effectively execute on these are frustrated by the inscrutable nature of the algorithms.

3.3 Communication

As has already been alluded to, various features of the algorithms used in big data analysis, make it difficult to understand the decisioning of the model. This is a problem for those building a model and those responsible for governance of a model, but it is even more problematic to

explain this to those affected by the model. This leads to the last relevant ethical concern identified namely the communication of the reasoning for any decision.

It is widely agreed that the reasons for any outcomes should be explained to those affected. Some of the ethical principles highlighted in the use of big data relate to transparency and communication. Any entity using the analysis of big data should be transparent about this practice. This can help to avoid public backlash when the public find out later on (Burston et al., 2020; Grindrod, 2016) and is therefore not just an ethical matter but also a matter of expediency. After disclosing that the analysis of big data has been used in decisioning, some authors go further and require that it be explained to the customer which factors informed the decision. The need to explain the results depends on the context in which the analysis has been used, however any decisions directly impacting customers financially, such as underwriting and pricing, would trigger fairly detailed disclosure. For underwriting and pricing decisions the key features that informed the decision needs to be communicated. This often required additional statistical models to be run and a field of statistics has developed to enable such explanations (Burston et al., 2020). This disclosure therefore places an additional burden on the institution using the models.

Such disclosures give the customer the opportunity to challenge the decision and present evidence to prove alternatives explanations.

In addition it is important to allow for an equitable distribution of the benefits of big data analysis between customers generating the data and companies using the data (Grindrod, 2016). Some uses may only benefit the companies performing the analysis. A prime example is social media companies providing their platforms to users for free; the “price” paid for their services is user data (Grindrod, 2016). Corporates, including life insurance companies, using data to

enhance their own profits should ensure that some of the benefit is transferred to those generating the data.

In this section three ethical concerns of the use of big data have been highlighted. These concerns may impact the justification of the practice of risk classification in the pricing and underwriting of life insurance. In section 4 the impact of these factors on the balance will be explored.

4. The justification of the life insurance industry using big data

The use of big data can result in a wide range of new practices, new risk factors or combinations of risk factors used in the pricing and underwriting of insurance. A single assessment of the ethics of all potential uses cannot be performed. However, the analysis will consider whether and how the ethical justification of pricing and underwriting presented in section 2 is modified by the three broad themes of potential ethical concerns with the use of big data introduced in section 3. The aim is to answer the question whether the use of big data to personalise risk in the pricing and underwriting of life insurance undermine the delicate balance of factors that allow the industry to be morally justified. Constraints on the use of certain factors will also be introduced.

Big data was defined in section 1.4 as the totality of the datasets, statistical techniques and the subsequent operationalisation of the algorithms in decision-making. The insights from such analysis often result from combining diverse datasets to draw out unique correlations. However, the general insights need to be applied to the attributes of the individual to give an indication of the risk. The sources of the data could at a superficial level impact the analysis; data from a fitness device tracking health or exercise behaviour may be more easily accepted to determine risk of death whereas banking and credit information may be more difficult to justify. This is described in more detail in section 4.5 dealing with how the results of such analyses should be communicated to customers and the effects this may have on the justification, however, as explained there the analysis seldom relies on a single factor that can easily be communicated.

4.1 Knowledge of the date of death

Before considering whether and how the ethical concerns with big data modify the ethical justification of the industry, it is worthwhile to consider the unlikely scenario where the

analysis of big data enables the accurate prediction of the date of death of individuals. Given that humans have attempted to predict the future without much success for most of their existence this is a scenario not very likely to happen in the foreseeable future. However, it is possible that in a society with advanced General Artificial Intelligence this knowledge may be revealed.

In such a world there will be little or no requirement for life insurance in its current form as elaborated by Wilkie (Wilkie, 1997). People will be able to save for their death or retirement and the pooling of risk to reduce the uncertainty of death would not benefit anyone. The ethical justification presented therefore by extension is nullified as the benefit for individuals of reducing the uncertainty of when they will die has now been achieved by obtaining certainty about this date.

However, two further variations of this scenario need to be considered, both involving asymmetry of the knowledge about the date of death. In the first the individual may not be privy to the knowledge of their pending death and in the second the insurance company does not have access to this knowledge. In addition, such knowledge can never be certain as an individual can die at any time from an unforeseen accident.

In the first case it would not be ethical for the insurer to use the information in the pricing and underwriting of insurance as this would reveal the future date of death to the individual. It is not clear whether individuals would want such information. Big data analysis requires large datasets which will not be in the possession of individuals. They will at most be aware of all the data pertaining to themselves, although few people actively record details of all websites visited, communications, transactions and history of places visited to name a few. This data combined with the data from millions of other users may provide insights into mortality; for example, identifying dangerous areas. The insights from such analysis will therefore always be

with the curators of large datasets such as governments, internet companies and other corporates.

Knowledge about when people will die will be of value to governments in order to plan services to citizens and to insurance companies who can use this information to price life insurance policies and manage their own risk exposures more effectively. If information about individual lifespans is ever revealed by such analyses, detailed consideration will need to be given to whether such information should be communicated to people as this will completely change the nature of a human life and the fabric of society.

Adorno discusses the right not to know in the context of the results of genetic testing, which may be predictive of future health conditions, although much less certain that the scenario described here. He shows that such a right not to know is not in contradiction of autonomy, but rather an extension of autonomy given that they have a legitimate interest in not knowing given the potential severe psychological impact this information can have (Andorno & Laurie, 2004). I would argue that knowledge about the date of death could be useful for some but devastating to others. A clear right not to know regarding such information will therefore exist. This right can also be used in a consequentialist theory, as the harmful impact of the information on those who choose not to know, will impact their individual and overall economic welfare.

However, given the exact nature of this information compared to the predictive nature of genetic tests, any use of the information in the pricing and underwriting of life insurance will reveal the date of death to the applicant of the life insurance. This means a right not to know translates to a restriction on using the information for customers who choose not to know. The market will therefore still resemble the current market.

In the case where the individual possesses this knowledge about the date of death, the market will not be able to function as a result of adverse selection. An example of a scenario where

the individuals know the date of death and private insurance companies do not would be where the government has this information and disclose it to individuals.

Therefore, in all scenarios where the exact date of death is known the life insurance market as it currently exists will not be able to function. In both cases where the information is known by individuals, the benefit of insurance can be achieved in other ways. In the scenario where the information is known by the company, the constraints imposed by the right not to know will prevent its use, and the ethical justification of the current market will still apply.

However, in more realistic scenarios involving the use of big data the impact of potential ethical issues introduced by big data on the consequentialist argument presented to justify the industry needs to be investigated.

4.2 Impact of increased efficiency and reduced cost on ethical justification

In many ways the analysis of big data makes the industry more efficient, reduce the costs and hence increase the overall economic benefit from the industry. Reduced cost can also extend the reach of the industry to people previously not in reach. This could be as a result of being able to provide smaller policies more cheaply or by including risks where monitoring could previously not be done at a reasonable cost. An example of the latter would be the monitoring of whether HIV positive lives adhere to treatment protocols to manage the disease. Providing insurance to more people will increase the economic welfare generated by the industry as explained in section 2.1 and is thus morally permissible.

To ameliorate the problems of asymmetry of information benefitting the applicant, several processes are introduced into the pricing and underwriting of insurance adding significant cost to the process and raising barriers of entry for interested individuals. Examples are long medical questionnaires and invasive medical testing. The results of big data analysis can arguably help

to swing the balance of information asymmetry in the favour of the insurer; the risk factors will be revealed cheaply, no expensive testing will be required, and the process of application can be focused on remaining areas of uncertainty. All of this will make the application process more streamlined, and hence accessible to more people, as well as cheaper. This will make the industry more efficient and enable it to provide more life insurance, which will enable more people and hence society to experience the benefit of insurance.

Although the research is focused on pricing and underwriting of insurance, many other uses of big data in the insurance industry will further reduce the costs of the industry and hence increase the economic benefit (Burston et al., 2020). In the following sections further restrictions will be placed on certain uses of big data in the pricing and underwriting of life insurance where these factors have certain repercussions on applicants and hence the size and feasibility of the industry. However, where big data is used by the insurer to manage the business with no direct impact on customers, fewer restrictions should apply. Any analysis aiding the estimation of risk will help the insurer to manage its risk more effectively. Ultimately this will make the industry more capital efficient and could result in lower prices to consumers. Insurance fraud remains a huge challenge to the industry and large amounts of money are spent annually to identify and fight such fraud. The analysis of data is already used to identify such fraud cheaply further reducing cost. Many such back-office uses of big data will arguably be identified over time. These will make the industry cheaper and more efficient, increasing the economic value of the industry for all and hence are morally justified.

The use of behavioural risk factors is becoming more prevalent in insurance (Meyers & Van Hoyweghen, 2018). In most instances such behaviours are expensive to confirm, and they need to be monitored over time. Again, big data makes it much easier and potentially cheaper to incorporate such factors into the pricing and underwriting of insurance. Apart from the efficiency benefits for the industry there are further benefits for society of improving negative

behaviours. As an example, providing a discount in premium rates to those who exercise regularly not only incorporate an accurate risk factor into the assessment of the risk of the insured but also improves the health of the individual and society, thereby increasing economic productivity and reducing healthcare costs. This will increase the economic welfare and hence is in alignment with the ethical justification of the industry.

4.3 Incorporating bias and discrimination into the framework

The effect of the three ethical concerns arising from the use of big data addressed in section 3, namely unintentional bias and discrimination arising from big data analysis, the treatment of individuals by reference to a group and the implications of overly precise inferences on the justification for the life industry needs to be considered. As discussed in section 3 the ethical concerns raised pose potential challenges in all applications and in this section, it will be shown how these challenges manifest in the in the pricing and underwriting of life insurance.

An argument has already been provided for why discrimination in insurance is justified in section 2; where the differentiation is based on risk classification this is required to avoid adverse selection. However, it has been stated that any laws prohibiting discrimination need to be adhered to. Therefore, when using big data, life insurers need to guard against introducing unintentional bias and discrimination into the pricing and underwriting beyond what are already deemed appropriate for use. Similar to other users of big data, appropriate controls will have to be put in place to identify such bias and techniques applied to remove it where identified. In the sections dealing with epistemic issues and communication it will be explained how additional factors predictive of the risk of applicants can be ethically introduced. However, the use of such factors should be intentional.

A specific area to consider is the bias introduced by certain groups not included in the datasets on which the analysis is based resulting in biased treatment by algorithms, as algorithms trained

on data excluding these groups do not know how to treat them. The analysis of mortality rates by life insurance requires data covering an extended period. Any discrimination or other forms of exclusion happening in the past can therefore easily be perpetuated. In addition, where alternative sources of data such as banking data or social media data are used further groups may be excluded. The consequentialist justification provided for the life insurance industry showed that more economic welfare is created by an increase in the size of the market. Given the diminishing marginal utility of life insurance for individuals, the benefits described in section 2.1 for individuals would be particularly pronounced if the reach to previously excluded groups is increased. Perpetuating this exclusion would therefore frustrate the ethical justification of the industry presented.

In addition, financial inclusion is a goal in South Africa (National Treasury Republic of South Africa, 2020). A conscious effort will have to be made to understand whether the analysis of big data is biased to groups as a result of limited representation in the data; methods will have to be put in place to correct for any under-representation. As current methods use more easily identifiable risk factors such as age, it may even be possible that algorithms calibrated using big data now decline insurance cover to people who will be able to obtain insurance currently. If this happened the economic welfare created by the industry would decline as the industry would now provide life insurance to fewer people, resulting in the application of big data being regarded as unethical.

The concern raised that the treatment of individuals is determined by membership of a group is less problematic for life insurance as the practice of risk classification is common in the industry and has already been justified. Risk classification as currently applied means that the premium rate charged to an individual or the underwriting decision about the individual is made as a result of possessing certain risk factors or belonging to the group of people having those factors. However, as will be explained Section 4.5, the additional requirements of explaining

the reference group informing any decision and providing the opportunity to challenge this will have to be met to enable ethical risk classification based on big data.

The last matter to consider is the ethical implications of overly precise inferences or as it is known in insurance, the personalisation of risk. Insurance is based on the pooling of risks, however as risk classification is refined the sharing of risk in any insurance scheme reduces and individuals have to pay more accurately for their own risk (Seekings & Pearch, 2020). It has been shown that in the extreme application of this scenario where the exact date of death of individuals is known, a voluntary insurance market is not possible. The use of risk classification using broad grouping such as age and gender has already been discussed, using different factors or more factors does not alter the practice substantively. Application where the date of death is not known will still involve pooling of risk, however, with a much smaller group. The original justification for this practice therefore remains intact.

4.4 Incorporating epistemic issues into the framework

The analysis of big data often reveals correlations in the data that cannot be explained (Mayer-Schonberger & Cukier, 2017). This could either be a correlation that is not backed by any theory or could involve multiple factors making it difficult or impossible to explain what combination and mix of factors explain the decision. Often the model builders may not even be aware of the factors being used and therefore cannot explain it either. The basis for the knowledge about such correlations is merely that it was revealed by the data and it cannot be defended from prior theory or knowledge. By applying the consequentialist justification put forward, it should be determined whether such factors can be used. As per the framework, an industry using such factors will have to be envisioned and the consequences of allowing for these factors on the overall economic welfare generated by the industry estimated. This process is described in the following paragraphs.

Currently applications for life insurance are either declined for certain medical conditions or advanced age, or a premium rate will be quoted based on the risk rating. These factors are however commonly understood and expected by most people to be used in the assessment of life insurance. Wilkie outlines the long process involved from identifying that a factor potentially impacting risk to actual use in the pricing of life insurance by reference to the example of the use of smoking status. The delay is as a result of the time it used to take in the past to build up sufficient data to prove the relationship at a high degree of confidence (Wilkie, 1997). This emphasises the need for certainty about the impact on risk prior to introducing any new factor. Big data analytics do not follow these extended timelines and in general substitute the need for data spanning extended periods by sheer volumes of data. In addition, the methods underlying big data analysis are particularly good at teasing out correlations between variables; there is no guarantee that such correlation implies any causation (Mayer-Schonberger & Cukier, 2017; Mittelstadt & Floridi, 2015). Specific consideration will have to be given whether similar reasoning for discrimination based on factors causing the risk of dying can be applied to factors merely correlated with the risk of dying; this is done in the following paragraph. One way to overcome the problem would be to perform the required research to understand the underlying causal relationships driving the correlations identified by the analysis. This will make it easier to assess whether it is ethical to use the factor and could be beneficial for society if the research enables the risk factor to be mitigated. An example is the steps taken to discourage smoking after the risk of smoking became apparent. However, the drawback with this approach is the time taken to perform such research, which could be decades. This inhibits the agility of big data analysis. The correlations identified may further often involve combinations of disparate factors requiring research across multiple fields. However, where this is practical it should be attempted.

Given that the correlations are identified from the data and not based in prior knowledge, the justification for risk classification based on such factors using adverse selection cannot be used. It is not known whether these factors could influence the risk of dying and as the correlations will not be known by those purchasing the life insurance, they cannot be used by individuals to inform adverse selection. Therefore, the impact of using such factors on economic welfare, the measure of value used in the justification of the industry, needs to be assessed.

In section 2.1 the different mechanisms through which life insurance contributed to economic welfare were described. Life insurance is instrumental in achieving certain benefits which can be achieved in other ways as well. However, for the purpose of this analysis it will be assumed that all other factors, such as the level of social security benefits available in a country, remain constant.

New factors revealed by the analysis of big data can influence the economic welfare generated by the industry through the benefit life insurance provides to individuals who have such cover; through the claims paid out by the industry to beneficiaries and through the impact of the overall size of the industry on the economy.

It will have to be assessed whether the use of such new factors increase or decrease the number of people who purchase life insurance compared to the status quo of not using such factors. The number of people will increase if the new risk factors enable life insurers to provide cover or reduce premium rates to affordable levels for individuals previously regarded as too risky. The number of people will decrease if the new risk factors enable life insurers to identify high-risk individuals previously regarded as having lower risk and either decline them cover or increase their premium rates to levels that may be unaffordable for some. The net impact of this could be an increase or decrease, but it is unlikely that the overall size will decrease as private insurers will aim to maintain their profitability which will be difficult to do for a much

smaller book. In addition, given that the industry has the operational capacity to administer a certain number of policies it is unlikely that they will be keen to contract this. A likely scenario is therefore that the size of the industry, as measured by the number of people granted insurance, will increase.

A difficulty with utilitarian theories is that they require interpersonal comparisons of utility (Sen, 1979). Although a person may be able to accurately rank different options in terms of utility, it is not simple to compare the levels of utility of different people. This difficulty also arises when considering the mechanism through which life insurance benefits individuals, by enabling certain economically productive behaviours. This is also relevant just considering the utility people get from having life insurance. Even if new factors identified from the analysis of big data increase the number of people with life insurance, the mix of people may be different. It will be assumed that this increases the economic welfare from the industry, without having regard to the situation where the change in mix actually result in a loss of utility.

New factors identified through the analysis of big data can also impact economic welfare through the mechanism of the benefits paid out to beneficiaries of life insurance policies. Given that the amount paid out is a function of the risk of dying of the lives insured, it is likely that this amount decreases. However, given that the premiums collected from all insured lives over time fund the benefits, it is conceivable that these amounts are returned in the form of lower premiums and hence flow back into the economy as well. Should the benefit of the lower claims from lower risk individuals not be returned in the form of lower premiums, but accrue to higher profits, the distribution of the benefits of big data should be considered as discussed by Grindrod (Grindrod, 2016). In such cases, at a superficial level of analysis the economic welfare may decrease although there may be second-order effects offsetting this.

From the above analysis it can be seen that the introduction of new risk factors based on the analysis of big data can cause economic welfare to increase, decrease or stay constant. Although no universal principles can be derived, any new factors increasing the pool of insured lives is likely to be morally justified based on the consequentialist analysis. If the overall expected claims from the pool of lives reduce, some of this benefit should be returned in the form of lower premiums offsetting the reduction in claims to ensure that the impact on the economy does not reduce. Any new factors causing the nett number of insured lives to reduce is likely to reduce the economic welfare from the market and is not morally justified based on the consequentialist analysis. As the overall impact on the industry cannot be accurately measured by individual companies this introduces a role for industry oversight. This will be discussed in more detail in section 4.5.

In addition, given the lack of theoretical validation and the tenuous nature of some of the inferences, the impact of incorrect inferences on the industry needs to be considered. Incorrect inferences may impact the profitability and sustainability of the industry. If risks were incorrectly classified and priced, this could lead to losses and reduced overall economic welfare generated by the industry. The framework therefore requires appropriate safeguards to be in place to avoid this and emphasises the care and diligence that need to be taken in any analysis of big data used in the pricing and underwriting of life insurance.

4.5 Incorporating communication into the framework

In addition to the impact of the introduction of a new factor on the size of the market as described in section 4.4, the impact on the life insurance industry needs to be considered when such information is communicated to customers. It has been stated that it is important to communicate that decisioning is based on the analysis of big data and which factors impact the decision in section 3.3.

Even if the risk factors used in the decisioning were not directly communicated to applicants of life insurance, the level of risk assigned to an individual would be evident in the price of the insurance or its availability. I have already dealt with cases where big data can be used *in lieu* of expensive testing to confirm medical declarations by applicants and this will not be considered further.

However, the impact of revealing a level of risk that the insured does not understand or is not aware of on the ethical justification of the life insurance market needs to be considered. If the industry uses big data analysis, applicants of insurance may now be declined insurance based on such factors. Similarly, the premium rates they pay will now be determined by such factors. Even if these factors can be explained, it will be hard to challenge given that they are not backed by scientific theory.

As an example, a seemingly healthy twenty-year-old may now be denied insurance or charged an exorbitantly high premium rate. The impact of the factors may also work in the opposite direction and insurance may be granted to those previously denied access. This will appear arbitrary to the applicant but will only be visible in extreme cases; as mentioned before, most people do not have a sufficiently nuanced understanding of how known risk factors should impact pricing and would not be aware of less severe adjustments to current premium rates.

Nonetheless, these extreme cases will be very problematic for those impacted. In addition to being denied insurance or charged very high premiums, given that the reason is not a well understood risk factor, other social benefits will not be available to compensate. As an example, the elderly or disabled who are currently often denied insurance are eligible in many countries for government benefits. Such benefits will not be available to those classified as high risk by factors identified from big data models. This will make the process of applying for insurance a very stressful experience as it may involve outcomes experienced as arbitrary; in addition, such

verdicts will cause great emotional anxiety as it communicates to the applicant that they are regarded as being at high risk of dying. This may discourage people to apply reducing the size of the industry. In addition, some people will not only be denied access to life insurance but also be denied the benefits provided by life insurance without the ability to obtain it through other channels such as social security. This will further reduce the economic welfare in a situation where unknown, seemingly arbitrary factors, impact the decisioning in life insurance.

When the basis for any decision is explained to the applicants, the effects described in the preceding paragraph may be reduced to a large extent. Careful explanation of the factors used in the decision, will give applicants the opportunity to challenge any such decision. Where factors cannot be explained or the explanation appears arbitrary, the same considerations as outlined in the preceding section should apply. A field of explainable Artificial Intelligence aims to develop methods to explain the output of complex models in understandable terms (Burston et al., 2020).

However, it could be argued that the inclusion of novel factors identified by the analysis of big data in pricing and underwriting decisions will expand the overall industry and this will more than offset the harm caused by unpredictable rulings; in this case the use of such factors will increase the economic welfare generated by the industry and thus be morally justified. This analysis suggests that any new factors improving access to insurance will be justified. The use of new factors that are easy to explain and only cause minor adjustments to the *status quo* will be justified. However, any new factors that may result in extreme outcomes is likely to cause reputational damage and do more harm than good.

This places the onus on the life insurance companies applying big data analysis to consider the implications of each new factor. The consequentialist analysis proposed requires the economic welfare of the entire industry to be considered, and it is unlikely that any individual life insurer

will have the incentive to do so. However, it should be noted that the life insurance industry is in general heavily regulated. In addition, industry bodies exist. It is therefore possible to get an industry view on any new factors to be introduced.

Two observations can be made to ensure that the use of such factors remain morally justified.

Firstly, if such factors were exclusively used to provide insurance to people that would otherwise be regarded as too risky, it could be guaranteed that the overall utility from the industry would increase. More people will be insured, and the negative impact of arbitrary declines or high premiums will be avoided. There will also be limited scope to adjust premium to reflect the increased understanding of risk, as long as these adjustments are modest.

Secondly, there is a role for regulators to consider practices across the industry and ensure that the overall practices increase the size of the market and do not harm customers. This will be difficult given the proprietary nature of many big data models. However, where it becomes apparent that practices are harming the reputation of the industry, or excluding certain types of people, such practices can be prohibited.

In summary, any such factors should be used with care.

5. Possible objections against the argument

In section 2, a consequentialist justification for the life insurance industry was presented. In section 4 it was shown how the consequentialist justification can be extended to evaluate the use of big data to enhance risk classification. It was also shown how further restrictions can be incorporated into the argument; these restrictions aim to address objections against the practice of risk classification in the pricing and underwriting of life insurance. Two objections to risk classification were addressed, namely, that the practice amounts to discrimination (section 2.2) and that it frustrates the objectives of social justice (section 2.3). These objections will be excluded from the discussion in this section.

Various objections are routinely levelled against the use of consequentialist theories; several of them also relevant for the argument presented in this paper. The one that will be addressed in detail is the objection that consequentialist theories are insensitive to the distribution of goods (Talbott, 2013). This is an objection against the consequentialist framework chosen to analyse the impact of using big data on the practice of risk classification in the pricing and underwriting of insurance.

In a paper illustrating the benefits of the capability approach, Sen highlights how the maximising feature of utilitarianism, as an example of a consequentialist theory, causes problems with distribution – as long as the gain from the winners more than offset the losses by the losers, such theories are silent about the resulting distribution (Sen, 1979). Other approaches such as using the 'maximin' criteria – maximising the amount received by the person who receives the least – has been proposed to overcome the problems with the maximising feature (Fleurbaey, 2021).

The consequentialist justification does not denounce scenarios where certain people are denied insurance. It was shown that because of adverse selection, risk factors that people are aware of,

such as serious disease, must be allowed for in the pricing and underwriting of life insurance, despite the further detrimental impact the exclusion from the market can have on the quality of life of those impacted.

It was already shown in section 2.3 that certain adjustments to the market, such as the practice of providing small policies without risk classification, can still be consistent with the consequentialist justification provided and this already provides a partial remedy to the objection. However, the more specific details of the distribution of life insurance benefits after making those adjustments still needs to be defended.

As a response to the objection, the following rebuttals will be presented. Firstly, the analysis deals with a private market for life insurance supplementary to the benefits provided by the state. While private firms should seek to promote the distributive aims of a government or society, they remain businesses with a profit objective. The economic benefits produced by such firms generate tax revenue for government which can help fund distributive projects. The consequentialist aim of maximising the economic benefits from the industry, therefore, implicitly maximises the tax revenue for government and further government's distributive projects.

Secondly, life insurance is a means to achieve other benefits and the hoarding of the benefit for its own sake has no value. The exposition of how life insurance benefits individuals in section 2.1 illustrated that it enables behaviours that bring about economic welfare for individuals; it is therefore not sensible for a few people to capture the market. This is also illustrated by the diminishing marginal utility of life insurance (Nyman, 2001). This means that the framework as applied will avoid extreme scenarios where the entire good is allocated to one or a few. Such examples where a few people receive the entire stock of a good while the majority receive nothing are often cited to discredit consequentialist theories (Sinnott-Armstrong, 2019). The

pricing also relies on the pooling of risk which requires a large number of people to reduce the uncertainty.

Lastly, it should be noted that the analysis of big data is likely to reduce costs of underwriting and pricing and through the superior understanding of risk reduce the capital life insurers have to hold to manage the underlying business. If these benefits were shared with customers in the form of lower premiums, big data analysis would make insurance more accessible.

A second objection that will be addressed is an objection against the argument justifying the use of big data using the consequentialist justification of the practice of risk classification. When incorporating big data, the central premise that the threat of adverse selection necessitates risk classification in pricing and underwriting becomes moot as new, previously unknown factors, identified by the analysis of big data cannot be used for adverse selection. The argument mostly relies on the impact on the industry and hence the value, measured by economic welfare, of introducing such factors. The justification of risk classification as presented in section 2.1 relies crucially on the premise that should known factors of risk not be allowed for in underwriting and pricing, individuals will use their knowledge about such factors to select against the insurer resulting in the experience of schemes deteriorating as more high-risk individuals find it advantageous to purchase the insurance and low-risk individuals exit the scheme. Where individuals are not aware of factors potentially increasing their risk, they cannot use these to select against the insurer. The threat of adverse selection therefore falls away and the full argument presented does not apply anymore.

As response to this objection, I would firstly note that as discussed in section 4.2 not all factors revealed by the analysis of big data are new, previously unknown, risk factors. In many instances the analysis reveals known risk factors or identify proxies for known risk factors. As an example, big data analysis can reveal health conditions, without the requirement for medical

testing. The factors used to identify the health condition may be new and unknown, but the individual is still aware of the condition and can use it as the basis for adverse selection. This section also talks about behavioural factors that can potentially be introduced using the analysis of big data. Individuals are often aware of how such factors impact their health and risk of dying and such factors can reasonably be expected to form the basis of adverse selection. The reasons for not including them currently are that they are difficult to verify and monitor; the analysis of big data merely enables this.

Sections 3.2 and 3.3 deals with the introduction of new factors revealed by the analysis of big data. As these factors are not known factors and are often identified by correlations present in the data, it is very likely that individuals are not aware of either possessing these factors or their impact on the risk being insured. This forms the basis of the objection as such factors cannot be used as the basis for adverse selection.

As response I would refer to section 4.5 where the importance of communicating the factors driving underwriting and pricing decisions was discussed. It was argued in that section that the use of factors that appear arbitrary when communicated are unlikely to benefit the industry and hence should not be used. Methods aimed at enabling the communication of new factors often relates the decisions back to simpler, known factors. The section also discussed how communication gives applicants the opportunity to challenge decisions made which requires agreement with the risk classification. This implies that they are aware of their increased risk, even if through knowledge of other factors than those identified by the big data analysis. Such knowledge about their increased risk would still enable them to perform adverse selection against the insurer. This leads to the observation that most factors influencing mortality and other health conditions are known, and big data analysis is unlikely to reveal new factors, it is mostly likely to disclose proxies for these factors and cheap and easy ways to identify them. It is also likely to provide a more nuanced understanding of certain factors. As an example,

combining knowledge of an unhealthy lifestyle with advanced age, may make the risk uninsurable compared to others of the same age. The affected individual is very likely to be aware of this increased risk. And thus, the objection is not valid.

Further objections may be raised against the use of big data or against the constraints against the unfettered use of newly identified factors proposed in section 4. Many of the objections against the use of big data has already been addressed in sections 3 and 4. The limited use of new factors will not be defended further as this was argued already.

6. Conclusion

In this report I investigated whether the use of big data to personalise risk in the pricing and underwriting of life insurance undermines the delicate balance of factors that allow the life insurance industry to be morally justified. The current private market for life insurance uses risk factors to determine access and price, and this is in many ways similar to discrimination. This practice, and indeed the entire industry, therefore, requires justification. Introducing big data into the industry to more precisely classify risk, by introducing new factors and combinations of factors, changes the industry in subtle ways. The aim of the research was to determine how the introduction of big data adjust the moral justification of the life insurance industry.

In section 2, I presented a justification for the current industry based on the consequentialist approach. I have chosen this justification as it allows further restrictions and adjustments to be incorporated. The section illustrates how life insurance can be instrumental in creating economic welfare, the measure of value used in the consequentialist argument. Adverse selection, where people use knowledge about their risk to buy insurance when the price does not fully reflect their risk, was shown to be a threat to the market and hence if such risk factors are not allowed for, the market cannot operate.

In section 3, I presented some of the ethical concerns identified from the literature dealing with the ethics of big data. Big data can be applied in almost any industry and introduce a host of ethical issues and concerns to otherwise simple industries. However, given the unique nature of the life insurance being already reliant on the analysis of data and dealing with sensitive medical information of applicants, some of the issues were found not to be relevant. Examples of such issues include matters such as privacy concerns and consent. However, others such as

bias and discrimination, epistemic concerns and communication requires detailed consideration.

This was done in section 4. First it was shown that should the technology and capabilities one day allow the date of death of individuals to be accurately predicted, the life insurance industry in its current form will not be possible. However, the benefits of life insurance in terms of economic welfare would be obtainable in other ways. Unintended bias and discrimination, beyond what was defended in section 2, needs to be guarded against in the same way and potentially using the same tools as by other industries using big data. It was then investigated whether the consequentialist justification gave any moral weight to the fact that big data analysis often reveals risk factors based on correlation rather than a theory proving causation. This was found to be irrelevant, but it was shown that should the introduction of such factors result in a contraction in the industry, their use will not be ethical. It was then shown that the communication of factors, which should be done, may similarly be problematic in certain instances. The resulting conclusion was that based on the consequentialist justification for the industry big data may be used, but the impact of introducing new factors needs to be investigated.

In section 5, dealing with potential objections not already covered elsewhere in the paper, it was considered whether the consequentialist justification for the life industry as adjusted for the use of big data adequately addresses distributional concerns. It was shown that given the nature of life insurance, a very skew distribution is unlikely.

It was also argued that the requirement of communicating factors influencing the underwriting and pricing decision, links the newly identified risk factors to existing knowledge about risk and emphasises that adverse selection remains a valid concern even when using big data.

Adverse selection played a key role in the consequentialist justification of the industry presented in section 2.

I have therefore argued that the use of big data to personalise risk in the pricing and underwriting of life insurance does not invalidate the justification for the industry. Additional considerations apply when new factors are introduced, and careful consideration should be given to ensure their use does not upset the balance of factors justifying the industry. The overall impact of factors on the size of the industry as well as the impacts of communicating unknown risks on the market needs to be assessed. More work is required to understand which types of factors should not be used.

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