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From pool to profile: Social consequences of algorithmic prediction in insurance

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Abstract

The use of algorithmic prediction in insurance is regarded as the beginning of a new era, because it promises to personalise insurance policies and premiums on the basis of individual behaviour and level of risk. The core idea is that the price of the policy would no longer refer to the calculated uncertainty of a pool of policyholders, with the consequence that everyone would have to pay only for her real exposure to risk. For insurance, however, uncertainty is not only a problem – shared uncertainty is a resource. The availability of individual risk information could undermine the principle of risk-pooling and risk-spreading on which insurance is based. The article examines this disruptive change first by exploring the possible consequences of the use of predictive algorithms to set insurance premiums. Will it endanger the principle of mutualisation of risks, producing new forms of discrimination and exclusion from coverage? In a second step, we analyse how the relationship between the insurer and the policyholder changes when the customer knows that the company has voluminous, and continuously updated, data about her real behaviour.

Keywords

Algorithmic prediction, Insurance of Things, InsurTech, shared uncertainty, profiling, information asymmetry

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Introduction: Social management of shared uncertainty

In the last 10 years, the field of insurance has been confronted with signs of a change that has been announced as 'disruptive', whose outcomes are still rather uncertain and largely unexplored. Recent techniques of algorithmic prediction are raising high expectations in insurance, but also putting under pressure its probabilistic model of risk calculation and distribution. As a consequence of procedures using machine learning and Big Data, new forms of prediction are spreading in different areas of our society. Approaches like Predictive Analytics claim to use machine learning to give precise indications about the future of a *single event or individual*, overcoming the limitations of current statistical techniques that only address averages and general trends (Mackenzie, 2015, 2016; Siegel, 2016).[1] This possibility can have deep consequences for the way to deal with uncertainty in all fields, but for insurance it might mean a radical change in its model, its function, and its social meaning.

The claim to produce individualised prediction is both exciting and frightening. It may lead to optimisation of the use of resources, to targeted prevention, and to effective planning, but also to bind the future with preemptive policies, that reproduce bias and reinforce discrimination (Anderson, 2010; Angwin et al., 2016; Amoore, 2013; De Goede and Randalls, 2009; Kleinberg et al., 2017; Koepke, 2016; Lum and Isaac,

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2016; O'Neil, 2016). In any case, it breaks with the current management of uncertainty based on modernity's idea of an open future, which underlies important institutions in different domains of social life (Beckert, 2016; Esposito, 2007; Koselleck, 1979).

Influential historical studies analysed how in modern Europe, starting from the 17th century, the rise of probabilities calculus reshaped the relationship with the future (Daston, 1980, 1987, 1988; Hacking, 1975, 1990; Porter, 1986). Relying on great numbers, sampling and generalisation, probability calculus made it possible to cope with the impossibility of knowing the future. Desrosières (1993), for example, showed that statistics-driven thinking became the foundation of modern institutions in many fields, giving rise also to the development of a social security and insurance system which is the object of our analysis in the following pages.

As Daston (1988: 162ff) argues, insurance became a reasonable and socially acceptable practice when it based its operations on the mathematical calculation of probability.[2] Starting from the uncertainty of individual cases, the laws of statistics showed that in the mass and over the long run, an order could be found in large numbers, and this made it possible to separate the rational and foresighted attitude of insurance from the temerity and unreasonableness of gamers. Insurance, in fact, identifies collective regularities that justify a mutualisation of risks, and spreads these risks making the damage financially acceptable to everyone. Even if the future remains uncertain, individuals and companies can take risks and plan their activities in a controlled and protected way.

Since the 19th century, insurance has played a crucial role in enhancing social solidarity and managing risk in the current 'sociétés assurancielles' (Ewald, 1986). The insurance system relies on limited knowledge (nobody can know the future in advance) and on a chronic condition of information asymmetry (the customers do not reveal to the insurer all information they possess). Risk-pooling, which uses the laws of probability to spread the cost of accidents over a large number of persons in homogeneous groups, is still the foundation of insurance practices (Corlosquet-Habart and Janssen, 2018). By putting together many cases, the costs of future claims are spread among all policyholders. The latter have an interest in joining the pool, because the future is uncertain and nobody can know in advance who will be affected by misfortune (that is, who will report what claim and when). Insurance offers a form of financial compensation to policyholders, inasmuch as it can balance the losses of the more unfortunate cases with the earnings of the luckier cases, and hope that in the end the difference will be to its advantage.

Recently, however, algorithmic techniques claim to offer individualised risk forecasts, which contrast with the probabilistic forms of calculation of risk over a more or less extended population. The problem, as *The Economist* (2015) expresses it, is that usage-based insurance (UBI) could 'call into question the basic logic of the insurance industry – that it is impossible to predict who will be hit by what misfortune when, and that people should therefore pool their risks.' A lively debate is dealing with consequences and challenges of algorithmic procedures for insurance industry and for the function of insurance in society as a whole (cf. Albrecht, 2017a, 2017b; Corlosquet-Habart and Janssen, 2018; Ewald, 2012; Lasry, 2015; McFall, 2019; McFall and Moor, 2018; Meyers and Van Hoyweghen, 2017; Siegelman, 2014; Thourot and Folly, 2016). The aim of this article is to participate in the debate by locating these phenomena in a broader social and theoretical frame, as a background for focused empirical research.

Besides analysing the actuarial literature and the research on the transformation of insurance (both from historical and sociological perspective), to develop our argument we studied the internal reports of insurance companies (Batty et al., 2010; Braun and Schreiber, 2017; Ewald, 2012; Italian AXA Paper, 2016; Keller et al., 2018); we interviewed managers of major insurance companies (e.g. the Internet of Things Practice Leader for Swiss Re and the founder of IoT Insurance Observatory); we analysed the current experiments in the offer of policies in Europe and the US (Vitality Drive, Fairzekering, Insurethebox, Snapshot); we followed the debate on prospected innovations in the field of insurance and the current studies on the interplay of Big Data and insurantial practice (François and Barry, 2018); we explored the technological developments in algorithmic prediction and their actuarial applications.

The article proceeds as follows. We open with a discussion of the possible disruptive effects of digital techniques for the model of insurance. In the next step, we explore the consequences of the use of predictive algorithms to set insurance premiums. Will it endanger the principle of mutualisation of risks, producing new forms of discrimination and exclusion from coverage? Referring to behavioural rates in car insurance, we then analyse how the relationship between the insurer and the policyholder could change if the latter knew that the former has voluminous, continuously updated, data about her real behaviour. Our main concern is that, whereas the function of insurance was that of a liberator of action encouraging enterprise and initiative, algorithmic prediction risks turning insurance into an inhibitor of action that discourages policyholders from embarking on actions.

A 'disruptive' change in the practice of insurance

The driver of the expected disruptive changes in insurance is digital technology, together with increased availability of data. Technical devices designed for other purposes,[3] such as black boxes for vehicles or smart watches for sports activities, can be used to collect data about policyholders' behaviour and to make individualised predictions, leading to adjustments in insurance rates for policyholders. The key formulas in this regard are InsurTech (the use of technology innovations in the field of insurance), UBI and Insurance of Things (IoT;[4] Boobier, 2016; Braun and Schreiber, 2017; Carbone and Silvello, 2018).

Insurance companies have an ambiguous attitude towards this particular use of digital technology. On the one hand, they perceive it as a great opportunity. They see InsurTech, for example, as a possibility for offering the customer a personalised policy, tailored to her lifestyle and proportional to her individual level of risk. The huge amounts of data that are produced incessantly by digital technologies should help companies build a 'profile' of their policyholders and develop specific offers for each individual case (Boobier, 2016; Keller et al., 2018; Marr, 2015).[5] According to François Ewald (1986), who studied the social consequences of modern insurance as a welfare institution, the combination of digital technologies and Big Data processing marks the beginning of a 'new era' in the history of insurance (Ewald, 2012: 15). Indeed, a number of scholars feel that the insurance sector is discovering a 'new world' (Ewald, 2012: 72; see also Corlosquet-Habart and Janssen, 2018; Ewald and Thourot, 2013; Ralph, 2017; Thourot and Folly, 2016: 65ff) that could radically change how companies design and sell insurance coverage.

On the other hand, these new opportunities also have the potential to become a threat, because they may question the principle of risk-pooling and risk-spreading on which the model of insurance is traditionally based.[6] Algorithmic techniques promise to offer each customer an individualised prediction of her risk profile and, with it, the possibility to pay the 'right price' that corresponds to her characteristics, conditions and behaviour, without having to pay for the other members of the group in which the statistical calculation placed her. This would endanger the very principle of risk-pooling underlying the modern insurance model. For the practice of insurance, the shared uncertainty that derives from the fact that nobody knows the future in advance is actually not only a problem (one that calculation can never remove, but only tame), but also the resource that makes it possible to develop a mutualistic way to deal with uncertainty. Individualised prediction threatens the entire insurance model. Insurance is, in fact, a 'business of uncertainties' (Ericson and Doyle, 2004: 148). The issue at stake here is not simply that insurance is a risky business: it is, more radically, one of how to make profit by dealing with uncertainty.[7] The complicated calculations that are made for the purpose of making allowance for uncertainty obviously do not change future uncertainty into certainty. Instead, they provide insurance companies with a sort of 'substitute for certainty'[8] that can be bought and sold.

In this phase of exploration and experimentation, any projection about the impact of algorithmic techniques on insurance is highly speculative. Scenarios built on the basis of technological possibilities risk not taking adequately into account the social consequences of the hypothesised innovations and sometimes not even the repercussions on the business model of insurance. This article is aimed as a provocation to highlight these aspects and discuss their implications. Our hypothesis is that if the way to make predictions – i.e. to cope with uncertainty – changes, then the way to insure also changes, with far-reaching consequences on the decision-making processes of insurance companies and on society as a whole. The following sections explore this hypothesis and its implications.

Discrimination and fairness

The principle of risk-pooling and risk-spreading on which the rationality of modern insurance is based has always oscillated between two opposing needs: on the one hand, the aggregation of all cases for compensatory purposes; on the other hand, the segmentation of the pool of policyholders on the basis of certain differences (such as gender or age) which enable more homogeneous risk classes to be defined. Segmentation offers two main advantages: on the one hand, fairer premiums based on the characteristics of the members of a segment (if females statistically drive more carefully than males, it is fair that they pay a lower insurance premium). On the other hand, the insurance company can be competitive by offering attractive policies on the private insurance market.

The problem, however, lies in the fact that segmentation is discriminatory by definition, because it is based on the use of differences that impact significantly on the price of coverage. The young male who drives safely can feel that he is being discriminated against, because his policy premium is calculated on the basis of gender and age and not on his actual driving behaviour. Social fairness does not necessarily coincide with individual fairness. These two concepts of 'fairness' clash and the conflict is exacerbated, rather than resolved, when the insurance company can rely on behavioural data (Barry, 2019; Frezal and Barry, 2019; Meyers and Van Hoyweghen, 2017).

Algorithmic prediction could radicalise the principle of segmentation, culminating in the extreme case of 'segments of one'. This would almost automatically mean the end of the risk-pooling on which the principle of risk-spreading is based (Albrecht, 2017a: 157ff, 2017b: 189ff; Charpentier et al., 2015: 57ff; Hay, 2015: 26ff; Houlle, 2015: 28ff). The consequences would be felt at two levels: in the attitude of individuals with respect to the insurance policy, and in the corporate policy of insurance companies. Here, we present some preliminary reflections on these two points.

1. On the individual level, the policyholder can be expected to refuse to share the uncertainty of her peers and to demand to pay only for her own uncertainty, leading to a demutualisation of risks that would undermine the solidarity aspect of insurance and produce a 'discrimination without intent' (Charpentier et al., 2015; Keller et al., 2018). The result would be that the individuals most at risk, and therefore most in need of insurance coverage, would have to do without insurance because it would only be available at unaffordable premiums,[9] while individuals at less risk would pay negligible premiums, as they would not need much insurance.

The effects could be paradoxical: those who knew they were running few risks and could be covered with little expense could pay for the insurance and then change their behaviour, for example by becoming more reckless when running a risk were more desirable or profitable than not embarking in it. When an individual knows that her behaviour is subject to forecasting (and even knows what consequences that advance information will have), she may be motivated to change her behaviour (Luhmann, 1980: 1069). But how could the insurer hide the result of prediction? In the case of insurance policies, the premium already works as a signal of prediction (Siegelman, 2014). It is therefore difficult to hide the result of individualised forecasting, unless the insurance company decides to adjust the premiums to the rates traditionally calculated on the basis of actuarial systems (in which case, however, the use of predictive algorithms would become superfluous).

If, on the other hand, the insurance company decided to communicate its individual prediction, the policyholder would have several options:

- to pay for coverage if the prices were very low and then not behave as predicted: as we said, this would force the company to admit that it had promoted adverse selection and moral hazard when its purpose, on the contrary, was to reduce them;
- to do without insurance if the forecasts were very favourable, but run the risk of being left without coverage if the claim events were to take place, contrary to the forecast;
- to do without insurance because the premium was too high.

In all of these cases, the disadvantages also affect the insurance company and the profitability of its business model.

2. From the insurance companies' viewpoint, the dilemma of future insurance could be to decide whether to offer a fair price on the basis of highly individualised predictions, but to the detriment of solidarity among policyholders, or to guarantee that solidarity, but at the expense of fair insurance premiums. In the opinion of many observers, 'there is no easy solution to this dilemma' (Keller et al., 2018: 12; cf. also Lasry, 2015: 22). On the other hand, if the mechanisms of risk-pooling and risk-spreading were to disappear, the fundamental pillar of what François Ewald (1989) called 'society of insurance' would collapse, with consequences that would affect the structures of society as a whole.

If in the future insurance data-driven predictions were to affect not only the reward system but also pricing, it could be awkward for insurance companies to justify decisions made not primarily on the basis of *causal relationships* (as in statistical data processing), but only on the basis of *correlations* (as in algorithmic data processing). The problem is made harder by the use of proxy data that work very well as predictors. For example, credit reliability (even when you simply pay bills on time) is an excellent predictor of careful driving (Brockett and Golden, 2007). The result can be surprising. The colour orange, for example, is an excellent predictor for good quality second-hand vehicles on the car market, probably due to the fact that those who choose such an unusual colour regard their car as a form of expression of their identity (Hardy, 2012).

Digital technologies enable the search for predictors to be multiplied by mining data, many of which are proxy data. Decisions made on the basis of these correlations, however, would be very difficult to justify, especially when such decisions include or exclude people in a highly selective manner. In the case of insurance, companies would have to justify *adverse exclusion*, i.e. the refusal of coverage for certain individuals due to characteristics that have no direct relationship with the object of coverage (Batty et al., 2010: 4, 13; Swedloff, 2014: 350ff, 366ff). On the other hand, if these correlations worked very well as predictors, how could insurance companies do without them?

This issue would probably end up being settled by the law, on the basis of rules and with outcomes that are not yet clear.[10]

Behavioural rates: Dilemmas of usage-based insurance

The availability of big quantities of data and techniques to process them also affects the relationship between insurers and policyholders. One of the most interesting novelties in current IoT is the so-called 'behavioural rates'. These rates are based on the use of self-tracking technologies, i.e. technical devices which produce real-time data about individual behaviour (Boobier, 2016; Lupton, 2016; Ralph, 2017). Well-known and increasingly common devices of this kind are 'wearable technologies', such as smart watches, and black boxes installed in vehicles.

Wearable technologies are discussed as tools for self-tracking in order to incentivise a healthy lifestyle for precautionary purposes. This type of coverage, called pay-as-you-live (PAYL),[11] however, is not actuarially strongly developed and represents a very limited, possibly unrealistic business (cf. McFall, 2019). Therefore, we focus our attention on the use of telematics data to improve ratemaking in motor vehicle insurance policies.

In the case of telemetry-based tracking devices, the policyholder must install a black box in her car.[12] This black box produces data about speed, braking, cornering, night-time driving and so on. Data is first translated into points. The policyholder also collects points when she takes her vehicle in for an annual check-up or completes a driving course. These points are then used to calculate a score (usually represented by a colour), which is communicated to the policyholder every month. If the policyholder achieves a high score, she receives some kind of reward, for example a fuel cash-back or a premium discount when she renews the car insurance policy. A low score is not penalising, although the denial of a reward is already in itself a kind of penalty. This kind of third-party liability car insurance coverage is called pay-*as*-you-drive (PAYD) when the reward system is based on how long you drive, and pay-*how*-you-drive (PHYD) when the reward system is based on how you drive.[13]

The relationship between score and personalised ratemaking is still under experimentation. First of all, telematics data do not replace traditional statistical-actuarial procedures (Picard, 2018: 96). Predictors extrapolated from telematics data integrate traditional statistical predictors, such as age and sex of the driver or vehicle engine power, in view of the possibility of finding strong correlations between past and future (Baecke and Bocca, 2017; Guillen et al., 2019a; Wüthrich, 2017). Unlike traditional statistical factors, signals based on telematics data are obtained directly from the behaviour of the insured, while classic statistical data only offers proxy variables with respect to the prediction of future events (Ayuso et al., 2016; Baecke and Bocca, 2017; Denuit et al., 2019; Gao et al., 2019; Guillen et al., 2019a; Ma et al., 2018). Taking this difference into account, some research (Verbelen, 2018: esp. 1300ff; Wüthrich, 2017: 1ff) has hypothesised that telematic predictors not only work better but could even replace statistical variables in the near future offering, among other things, an effective strategy to circumvent the European legislation which prohibits the use of gender as variable in the pricing of motor insurance policies as a discriminatory practice. These risks of unfair use of algorithmic procedures must be carefully monitored.

Already at this stage, however, behavioural rates in motor insurance policies offer an opportunity to shed light on the ongoing transformations in the insurance business model. At first sight, these are very similar to traditional 'no-claims bonus' reward systems (if you drive safely and do not report any claim, you receive a premium discount upon renewal of your insurance policy). Yet there is a difference. The no-claims bonus system is based on *accidents*. Consequently, the basic difference that drives ratemaking is 'it happens/it doesn't happen'. The PAYD reward system, instead, is based on *behaviour*. The basic difference is 'safe/unsafe'. From a temporal viewpoint, in the former case a reward is offered *after* the end of the insurance period, while in the latter case a reward is offered *during* the whole period of insurance coverage.

In our opinion, these differences have far-reaching effects on insurance mechanisms. The production of a score starting from data generated by the policyholder's behaviour and the need to base the reward system on the score achieved, together affect the relationship between the insurer and the policyholder first of all in terms of *communication*. We focus here on four consequences.

1. *The use of digital technologies and Big Data processing might reverse the information asymmetry* which has always been a crucial problem for the insurance industry. 'Information asymmetry' notoriously refers to the situation in which insured persons have information about themselves and their own risk conditions that they do not disclose to the insurers.[14] Since the company is incapable of accessing information that is known only to the policyholder, it runs the risk of selecting individuals who are more exposed to danger (adverse selection), thereby increasing its burden in terms of claim losses (Zweifel and Eisen,

2003: 320ff). Information asymmetry is, moreover, the underlying cause of *moral hazard* (Arrow, 1971a: 202ff, 1971b: 142; Heimer, 1985; Stiglitz, 1983: 6). A person who knows that she is covered by insurance is more inclined to run risks, affecting the probability of claims and the amount of overall losses to be borne by the company.

This asymmetry could be reversed with digital technologies (Lasry, 2015: 23; Siegelman, 2014: 317ff). The availability of large amounts of data and the ability to process them algorithmically could enable insurance companies to know much more about the policyholder than the policyholder knows about himself. The possibility for the company to be informed about the policyholder's behaviour throughout the whole period of insurance coverage could lead to a condition in which the problem of moral hazard could be, if not resolved, at least 'technically controlled' (Van Hoyweghen et al., 2006: 1231). In this hypothetical scenario, wearable technologies and telemetry-based technical devices would reduce or even remove the problem of imperfect information about the policyholder's behaviour (Stiglitz, 1983: 5), and the business of insurance would benefit from it (for example, by improving the detection of fraud).

On the other hand, however, the availability of virtually perfect information about customers' behaviour could lead to a condition in which the very possibility of insurance would be eliminated. If the forecasts were so precise as to eliminate uncertainty, there would be no interest in buying or selling a policy that exactly matches the level of risk: individuals would instead be expected to turn to financial instruments to organise their private security. Moreover, customers would be inclined to monitor the offers made by insurance companies as a way of obtaining information about their risk profile, potentially starting a feedback loop in predictive procedures, with unpredictable and maybe paradoxical outcomes.

2. *If personalised policies became so common as to be normal, privacy would become a luxury good that only wealthy people could afford* (O'Neil, 2016: 170). The policyholder may decide not to provide the insurance company with data by refusing to install a black box in her vehicle. In this way, however, she voluntarily opts out of the reward system and risks paying more than those who consent to installing a black box – and must be able to afford it.[15] The underlying reasoning would be 'if you want privacy, you have to pay for it'.

But the alternative of providing insurance with behavioural data is not without flaws and complications. Continuous monitoring of personal behaviour can be perceived in the long run as an interference with the right of *self-determination* (Keller et al., 2018: 12; Steiner, 2018: 75). The close dependence established between reward/punishment and individual behaviour means, in fact, that precautionary reasoning (exercising to avoid common chronic diseases, driving safely to avoid accidents) transforms the 'proactive' logic into a veritable 'aggressive' logic (Kerr and Earle, 2013: 69).[16]

3. *Behavioural rates would change the reciprocal claims and expectations of both insurance companies and policyholders, raising an issue of transparency*. What would happen, for example, if the policyholder stated that she did not report any claim *because* she drove safely, while the insurance company stated that she drove unsafely *although* she did not report any claim? Because discrimination would no longer be based on the occurrence (or non-occurrence) of an accident but on behaviour, the insurance company should at least justify how it could determine what is safe and what is unsafe when it processes data by means of algorithms (Scism and Maremont, 2010).

Actuarial mathematicians themselves are aware of the complexity of the data processing that allows them to find reliable signals that are strongly correlated to future claims. Assuming, for example, that risk exposure is directly proportional to the number of miles travelled by car (as is the case with PAYD policies) is questionable because as the number of miles driven increases, so does the driver's experience (the so-called 'learning effect'), with the result that the number of accidents decreases while the number of good drivers increases in relation to the frequencies expected if the ratios were directly proportional (Guillen et al., 2019a). At the same time, some actuarial mathematicians suggest to consider also the correlation of telematics data with so-called 'near-miss' events, i.e., narrowly avoided accidents, as the latter would be strictly correlated with the risk of being involved in future car accidents (Guillen et al., 2019b). The underlying reasoning would be that those who often come very close to having an accident should be treated as those who already claimed, although there has not (yet) been any accident.

4. *The combination of a telemetry-based definition of safety and behavioural rates can lead to paradoxical effects*. Consider a mother who drives to pick up her son from the nightclub and bring him home, travelling by car at night on busy roads where accidents often occur due to the abuse of alcohol and drugs. A

PHYD policy would penalise this behaviour, considering it unsafe.[17] The paradox is that this carelessness would be the result of a careful behaviour that is difficult to dispute. Even if the individual driving behaviours were motivated, there would be no solution to the conflict between the *carefulness* perceived by the mother and the *carelessness* calculated by the algorithm. For insurance companies, it would be difficult to motivate this interference in the family's daily life by deciding what its members may (or may not) do. Some people, such as bakers, would be penalised both in the case they installed a black box (which would detect an excess of night-driving behaviour), and in the case they did not agree to do it (because they would lose the opportunity to take advantage of rewards). This 'in-both-cases' penalty would rightly be rejected as an unfairly discriminating assessment.

Overall, the analysis of possible consequences of personalisation in insurance practices gives rise to a reflection about the *function of insurance*. The underlying reasoning of PAYD and PHYD rates could be formulated as follows: 'If you want to pay less, reduce your exposure to danger'. This reasoning, however, may be in contradiction with the meaning of insurance.

From the very beginning, the function of insurance has never been to remove the possibility of damage – in this respect, various forms of precaution are more useful, such as wearing a helmet when you ride a motorcycle or checking the conditions of river banks to avoid flooding. Instead, insurance invites those who embark on some enterprise to envisage alternative possibilities in case the final outcome should be ruinous (Cevolini, 2019; Esposito, 2009). The argument goes: Even if things may go wrong and I am aware of it, I will be covered by my insurance, and this encourages me to act. A future damage, thus, is not simply an obstacle but becomes the starting point to consider possible courses of events which include, rather than exclude, worst case. In this respect, as Ewald (1991: 208) points out, insurance works as a *liberator of action*.

The question now is whether individualised prediction risks turning insurance into an *inhibitor of action*, since the effect of a behaviour-based tariff could be to discourage policyholders from embarking on actions which somehow expose them to danger. This contrasts strikingly with the social function of insurance. In addition to the usual advice to 'limit hard braking' and 'avoid late night driving', for example, the common American PHYD car insurance policy Snapshot[18] suggests that policyholders should 'drive less overall'!

This possible inhibition resonates with the widespread concern that predictions can have the preemptive effect of 'diminishing a person's range of future options' (Kerr and Earle, 2013: 67). Typical cases are no-fly lists or judges' decision not to parole inmates. In such cases, what is limited (and eventually removed) is not only the possibility of damage, but also the possibility of action on the part of all those involved. Similarly, if the proactive effect of personalised insurance was to affect the behaviour of individuals in order virtually to remove the possibility of damage, a number of risky behaviours would be eliminated at the outset, along with the related opportunities. Truly innovative entrepreneurial initiatives or alternative lifestyles would risk becoming untenable from an insurance viewpoint, or they could only be undertaken without any coverage against possible damage, which would discourage many from embarking on them. Proactive insurance, in other words, would have the effect of contracting, rather than expanding, the space of imagination on which the innovative potential of modern society largely depends.

Closing remarks

The development of algorithmic forecasting techniques poses several challenges to the social function of insurance. Intriguing opportunities are accompanied by large areas of uncertainty and by new and still unexplored risk dimensions. Risk is unavoidable: even if insurance companies give up using InsurTech or postpone the decision, this itself is a decision that could have disastrous consequences on the company's competitiveness and on the possibility to offer effective coverage.[19] At the same time, InsurTech could mean the end of the institution of insurance – at least as we have known it over the last three centuries.

The other side of the enthusiasm for the possibility of satisfying the insurance industry's 'voracious appetite for data' (Swedloff, 2014: 341) is a certain hesitation when faced with a 'fathomless future'. For the time being, the only certainty is that the form of insurance will be involved in the ongoing changes. Whether insurance companies decide to do without digital technologies or to invest in them (as is already the case) and gradually adapt their business model, they are called upon to react, with wide-ranging effects on the social way to manage the uncertainty of the future.

At the present stage, however, it is important to distinguish between two issues: what many analysts say *could be done* with digital technologies, and what insurance companies *are already doing* with digital technologies. The use of Big Data has produced a big narrative about the predictive capability of the algorithms used to process these data. According to some observers (Siegelman, 2014: 325), this predictive power is 'grossly exaggerated', because social regularities are much more irregular than the regularities of the natural world, and the future remains unpredictable even when (or just when) we do everything possible to predict it. Moreover, predictive algorithms have not yet been applied to what is perhaps the most sensitive and crucial operation of the entire insurance mechanism: pricing. As McFall and Moor (2018: 205) rightly observe, it is premature, at least empirically, to come to the conclusion that premiums are tailored to individual policyholders in connected insurance.[20] However, it is maybe not premature to ask what could happen if such a tailoring of policy premiums would replace traditional actuarial practices, when one bears in mind that, as McFall (2019: 54) points out, price personalisation would personalise access to goods and services (e.g. care, credit, retirement benefits) as well.

In our opinion, the relationship between prediction, price and personalisation with which the digital society is confronted is the outcome of a more general socio-evolutionary dynamic depending on the internalisation of attributions which is characteristic of the risk society (Beck, 2005; Luhmann, 1993). In the case of insurance, the basic problem is always how to avoid adverse selection, i.e. the choice of particularly risky clients that will cost the company much more than the company has earned from the insurance premium. What is new in digital insurance is not so much that insurance companies try to predict risk in order to select the best cases in advance, but rather that the prediction is calculated directly on individual behaviour. External variables such as gender, age, race or place of residence are replaced, as we have seen, by internal, i.e. behavioural, variables. And the insurance premium could be calculated accordingly. While some observers claim that this would be justified for reasons of fairness (those who take more risks should pay more), others fear that the personalisation of prices could shape life-chances and produce new forms of discrimination. Unlike the traditional stratification into social classes, where discrimination was an assumption that affected individual life-chances, with the new alliance between actuarial techniques and digital technologies, discrimination would rather be a consequence of individual life-style, and generate classification situations that would affect individual life-chances in ways that are still largely unpredictable (Fourcade and Healy, 2013: esp. 560ff; cf. also Moor and Lury, 2018).

In any case, the possibility of replacing the assessment of the average with the assessment of the policyholder profile introduces a new way to deal with the uncertainty of the future. Empirical research is needed to observe whether this alleged *epistemological revolution* (Ewald, 2012: 10, 23) generates a concomitant *pragmatic revolution* – pragmatic both in the sense that insurance rates are calculated on the basis of the policyholder's actual behaviour, and in the sense that her behaviour is conditioned by the fact that she knows that the price of the policy depends on that behaviour. This in turn could have circular effects with far-reaching consequences on social institutions, on the forms of solidarity and on the relationship with the future in the digital society.

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Notes

1. Strictly speaking, machine learning procedures only have the purpose to extract patterns from data. These patterns can be used to test systems and improve them starting from mistakes. The approach of Predictive Analytics claims to go further and to use these techniques to make individual predictions.
2. For a critical discussion of Daston's argument, see Clark (1999); McFall (2007, 2011).
3. McFall and Moor (2018: 197) speak of 'outsider technologies', i.e. technologies that 'were not developed with insurance in mind'.
4. The acronym 'IoT' for Insurance of Things is commonly used in the literature in the field, intentionally playing with the ambiguity with the Internet of Things: Cf. Boobier (2016: esp. 15). See also https://www.the-digital-insurer.com/blog/insurtech-insurance-of-things-how-iot-shows-prevention-is-better-than-cure-for-insurers/ (last retrieval 18 February 2020).
5. The issue of personalising policy premiums is controversial, first of all empirically. We come back to this point in the conclusions.

6. 'Insurance is the paradigmatic risk-spreading institution' (Baker and Simon, 2002: 7). This principle actually precedes the modern form of insurance. Already in the mid-15th century, Benedetto Cotrugli ([1458] 1602: 75) suggested it would be wise 'to insure continuously every ship, because one supports the other, and in many [cases the insurer] can only gain' ('assicurare al continuo, & sopra ogni nave, perché l'una ristora l'altra, & di molti [casi l'assicuratore] non può che guadagnare').
7. What Pascal (1954, n. 451: 250) said about the gambler also applies to insurance: he 'ventures with certainty to gain with uncertainty' ('hasarde avec certitude pour gagner avec incertitude').
8. According to D'Amador (1837: 32), 'probability is, somehow, only the surrogate for certainty' ('la probabilité n'est en quelque sorte que le substitut de la certitude').
9. This scenario would be particularly problematic in cases in which insurance is mandatory and people cannot opt to bear their own risk.
10. In the case of genetic information, many countries worldwide have adopted regulations restricting access for insurance companies in recent decades (Blasimme et al., 2019). Such restrictions, however, mostly do not cover the use of Big Data in general, as for example information obtained in precision medicine studies.
11. Cf. Arentz and Rehm (2016), Ernst and Young (2015) and Frary (2019) focus on the German case. A frequent PAYL is the Vitality Health policy offered by the South-African insurance company Discovery.
12. Or a phone app: see Van Hoyweghen and Meyers in this special issue.
13. A good example is the Vitality Drive policy also offered by the South-African insurance company Discovery. See also the Fairzekering policy extensively described by Meyers and Van Hoyweghen (2017). Some insurance companies, such as Ingenie or Insurethebox, offer PHYD policies for newly licensed young people who are guaranteed a significant discount upon renewal of their policy if they drove prudently in the first year. The score, from 0 to 100 points, is communicated every 10 days and is divided into the colours green, light green, amber, orange, red and black. Cf. Stott (2016).
14. In his *Discours préliminaire* (preliminary discourse) to Pothier's well-known *Traité du contrat d'assurance* (*Treatise on the Law of Insurance*), Jean-Julien Estrangin (1810: xiv) pointed out that the insurer is forced to bargain 'so to speak, blindly with the policyholder, who alone has the secret of his business and the intimate knowledge of facts concerning the insurance.'
15. A partly similar issue is discussed by Blasimme et al. (2019) with reference to people's propensity to enrol in health-related studies and, specifically, in precision medicine research. Fearing that insurance companies may have access to their biomedical Big Data and that they may be denied insurance coverage, some people may become reluctant to participate – thereby also losing the advantage of receiving relevant findings about their health.
16. Moor and Lury (2018) speak of a 'dynamic disciplining function' in price personalisation.
17. Of course, driving at night is not the only parameter used in PHYD policies. However, a number of actuarial studies shows that night-driving is one of the most crucial signals, along with distance driven above the speed limit and distance travelled in urban zones, correlated with future claims (see Baecke and Bocca, 2017; Denuit et al., 2019: 386ff; Verbelen, 2018).
18. Snapshot is offered by Progressive. The motto is 'Drive safe and save. Drive extra safe and save even more.' See https://www.progressive.com/auto/discounts/snapshot/ (last retrieval 7 May 2019).
19. According to Thourot and Folly (2016: 201), 'the disdain [of the Big Data revolution] is a threat' for the insurance industry.
20. See also McFall (2019) on the Patient Protection and Affordable Care Act 2010 (ACA), widely known as 'Obamacare'.

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