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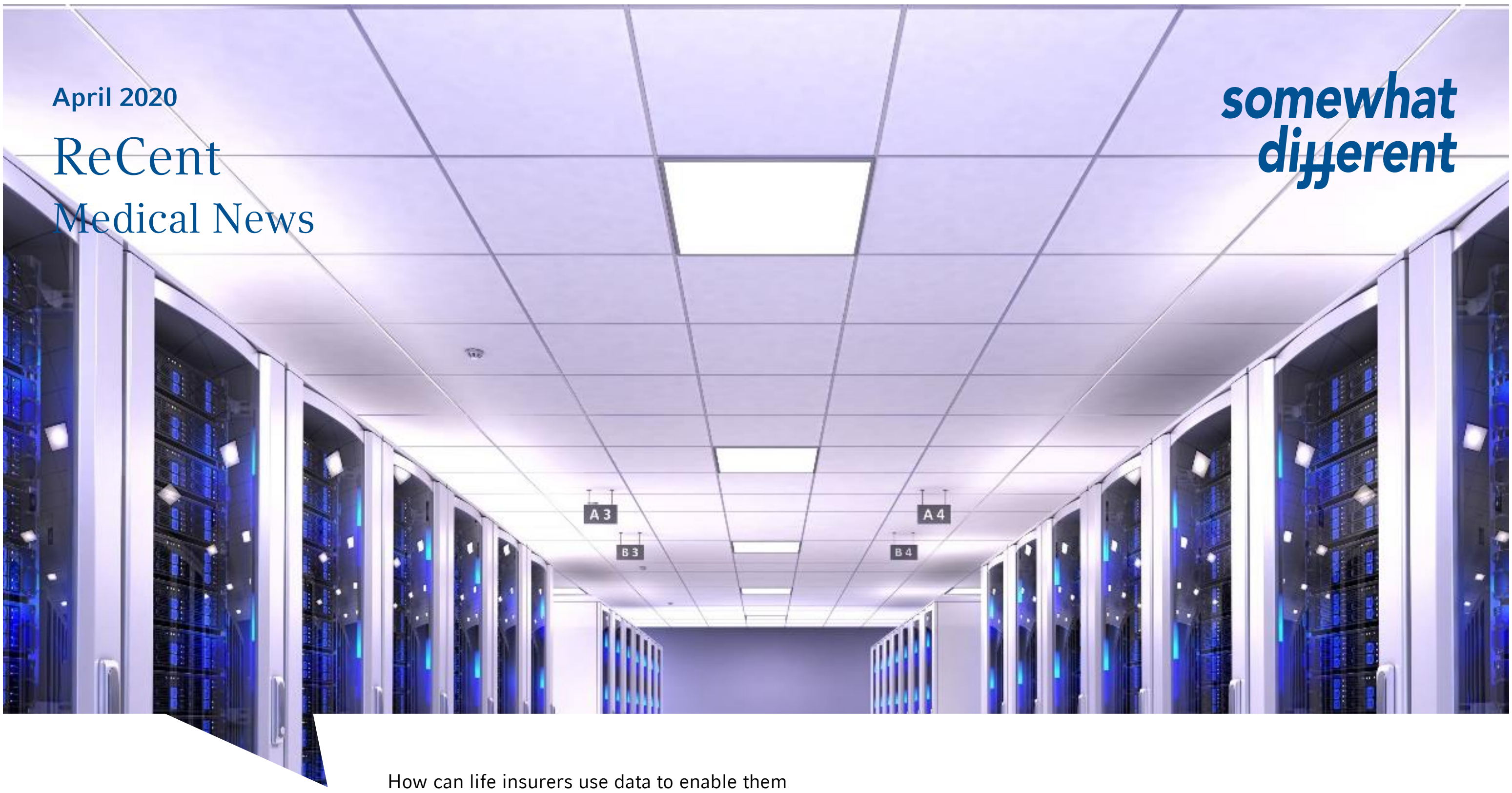
somewhat different



How can life insurers use data to enable them to become the insurers of tomorrow?

Data-driven insurance
From data delusion to data solution (part 1)

The Value Intangibility Paradox (VIP) refers to the fact that life insurance as a product has proven its value over time, yet for most people, (even those who will benefit in the future) its value is intangible.

Let’s imagine life insurance in the year 2035

Jenna, a 34-year-old mother of two, is given a promotion that comes with increased pay. Following receipt of her salary she gets offers from four life insurance companies including her current insurer. The latter offers her increased mortality and morbidity benefits that are commensurate with her new level of remuneration. As Jenna granted her insurance company access to her financial information, medical information and the health metrics from her wearable device, underwriting has been automatically concluded without any traditional insurance requirements. The other offers are subject to Jenna granting the same access to her data, which she does.

Within one minute of consenting, Jenna has four final offers and then makes her decision. Immediately, she receives her policy documentation which guarantees claims will be paid provided definitions are met and premiums are up-to-date – in other words, no post-issue contract validation, even if there is a claim tomorrow.

Without even filling out an application form, how did Jenna end up with a fully underwritten product at the best price with a claims guarantee? Her insurer used her data and returned it to her as a useful product.

We have all heard terms such as "big data", "data-driven", "artificial intelligence" and "machine learning" being used quite indiscriminately. But what do these terms really mean, and how can life insurers really use data to enable them to become the insurers of tomorrow?

This two-part article aims to review some of the important concepts and considerations for insurers wishing to use data and technology to make the necessary advances in insurance, including data ethics, data sources, the intelligent use of data, and the consequences of poor data-driven product design.

Introduction

As part of creating systems and building civilisations, humans have always created, needed, and consumed data. What has changed over time, however, is the nature, volume and frequency of the data created, needed, and consumed. Advances in technology have caused a proliferation of data sources and thus, data itself. The result is that we live in a state of data dependence, defined as “the situation in which you need something all the time, especially in order to continue existing or operating.”[1]

[1] See https://dictionary.cambridge.org/dictionary/english/dependence

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Our dependence on data will only increase with time, and as life insurers our offering and customer experience need to match the expectations of our current and future policyholders in order to remain relevant and fulfil our mandate of providing financial security.

Two key areas of insurance operations, underwriting and claims, stand to benefit the most from the proliferation of medical data, which is increasingly originating solely from digital sources. However, the VIP could also be solved as a side effect.

The proliferation of digital medical data, including from wearables, also implies the ability to obtain longitudinal medical information of policyholders with the potential for insurers to redefine themselves as health managers, rather than 'just' claims payers.

In other words, the often substantial period of time for which a policy is on the books creates an incredible opportunity to add significant value to policyholders by encouraging actions that lead to better health, and thus lower mortality and morbidity. Enabling a longer healthier life simply cannot be compared to a financial payout on a claimable event.

However, as great as the opportunity is, there are potential pitfalls and unintended side effects that could befall even the most well intentioned life insurer if the use of data is not well considered.

The purpose of data, simply put

> "The best way to use a person's data is to return it back to them as a useful product."[2]
>
> DJ Patil

While this statement intuitively makes sense, executing it is not simple. If we focus specifically on two phrases this will be apparent:

Phrase 1: "(…) use a person's data (…)"
Phrase 2: "(…) as a useful product (…)"

[2] See DJ Patil, Minds + Machines, Nov 2012

In order to use a person's data you need to acquire it, and then to return that data as a useful product there are many steps and processes that need to be followed. The question you should immediately ask yourself is "what data do I want to acquire", and to answer that question you need to ask another question "what problem do I want to solve and can I solve it with data?"

Remembering Jenna, let's look at key concepts and considerations as they relate to data.

Perceptions of data

In many respects we already live in a data-driven world; however, data can be, and has been, used with unethical intentions and purpose. In other words, data can be used to benefit users but it can also be used in a way that does not benefit, and even harms or prejudices, users.

It is also important to highlight that information and knowledge are not scarce resources in the information age we live in. People's attention, however, is a scarce resource. For this reason, we are often exposed to stories and news that grab our attention and, rather than getting a balanced view of the world, it is generally shocking or negative stories that make up the bulk of what we see.

When data use goes wrong, and the need for regulation

An excellent example of why organisational data use is viewed in a negative light is a 2018 scandal in which it emerged that a data analysis company had harvested the personal data of millions of social media users without their consent, using it for targeted political advertising purposes.[3] This is a prime example of how a person's data can be used – to develop a product – in an unethical manner with malicious purpose.

Unfortunately, as a result of events and news like this, the public perception of data use inevitably turns negative and invokes a cautious, highly legislated approach. Different countries have enacted their own data regulation laws in order to protect people's personal data. One example is the General Data Protection Regulation (GDPR) enacted in Europe. A discussion of the various regulations falls outside the scope of this article; suffice to say, however, that an individual's personal data is treated as an asset that they own

[3] See Wilson, R., 2019, July. Cambridge Analytica, Facebook, and Influence Operations: A Case Study and Anticipatory Ethical Analysis

and that must be protected, used only (with their consent) for the purpose for which consent was granted and any deviations can saddle companies with significant financial penalties.[4]

Despite extensive and thorough legislation to protect people's data, events such as the above-mentioned scandal significantly erode trust and detract from the many positive advances made possible by technology and data. This is something which life insurers need to be very aware of when building data-driven solutions, especially because medical information (a particularly sensitive category of information) will be used.

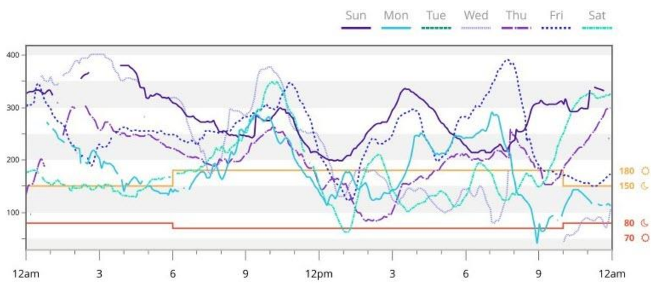
Given the negative perceptions around data use, this makes it all the more important that we emphasise significant and positive uses of data for the benefit of people, some of which are highlighted below.

When data use goes right

Despite the bad press that can easily overshadow the good we can achieve with data, it is important to highlight some ways – both big and small – in which data has changed, or is trying to change, the world in which we live.

1. Genomics (the study of our genome) emerged in the 1980s at the confluence of genetics, statistics, and large-scale datasets. Nucleic acid sequencing, and the data generated, enabled the discipline to assume one of the most prominent positions in terms of raw data scale across all the sciences.[5]
2. Attempts are being made to use anonymised data to predict the suicide attempt risk. "Traditional approaches to the prediction of suicide attempts have limited the accuracy and scale of risk detection for these dangerous behaviours. We sought to overcome these limitations by applying machine learning to electronic health records within a large medical database."[6]
3. A simpler yet highly effective example is continuous glucose monitoring, where a device regularly tracks glucose levels in diabetics and allows for informed decisions to be made in terms of lifestyle and/or treatment changes based on summary metrics and visualisations produced to aid decision making.[7]

Visualisation depicting automated glucose monitoring*



*Lee, V., Thurston, T. and Thurston, C., Methods of information in medicine, 56(S 01), pp.e84-e91. A comparison of discovered regularities in blood glucose readings across two data collection approaches used with a type 1 diabetic youth. 2017

4. Open source frameworks allow researchers and developers to create powerful apps for medical research.[8] When comparing traditional research with research involving this technology, clear benefits can be identified such as digitising the recruitment process, removing the need for onsite follow-ups, automating data collection, and reducing the study dropout rate. Considering the reach of wearable technology and the advances made in this field, the scope of the research potential is mind-blowing when we remember that the "smart wearable" market is expected to reach worldwide sales of USD 53 billion in 2019. Similarly, if we look at smart glucose monitors, smart BP monitors and various other devices that automatically upload data via apps, the average consumer becomes a valuable study participant.[9]

These are all examples of returning a person's data back to them as a valuable product.

[4] See White, L., et al., Overview of GDPR – key Points to Note, February 2018
[5] See Navarro, F.C. et al., Genome biology, 20(1), p.109. Genomics and data science: an application within an umbrella. 2019
[6] See Walsh, C.G., et al., Clinical Psychological Science, 5(3), pp.457-469. Predicting risk of suicide attempts over time through machine learning. 2017
[7] See Lee, V., et al., Methods of information in medicine, 56(S 01), pp.e84-e91. A comparison of discovered regularities in blood glucose readings across two data collection approaches used with a type 1 diabetic youth. 2017
[8] See Introducing Research Kit, http://researchkit.org/
[9] See Retail revenue from smart wearable devices worldwide 2014 and 2019

In summary, we have seen what the purchase of insurance may look like in a few years' time, and we have framed the age-old problem of the VIP inherent in the purchase of insurance. We have also discussed what the purpose of data is as well as how the use of data can be – and has been – negatively perceived, thereby creating a need for regulation. In addition, we have looked at a few use cases of data that highlight the positive effects, both present and future, of the use of data in medicine and research.

In **part 2** of this article we will continue on the journey from data delusion to data-driven insurance…

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