

THE EUROPEAN

N° 45

MAR 2026

ACTUARY

QUARTERLY MAGAZINE OF THE ACTUARIAL ASSOCIATION OF EUROPE



HEALTH

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USING MODELLING FOR A HEALTHY FUTURE

70% REDUCTION IN LONG-TERM SICKNESS, THE PFA APPROACH COMBINING AI + HUMAN EXPERTISE

With health measurements increasingly focussed on prevention of long-term incapacity, **Camilla Holm of PFA Denmark** spoke to **The European Actuary** about PFA's successful strategy combining health professionals' experience with data scientists' modelling, leading to a 70% reduction in long-term sickness. She highlighted the importance of using measures focused on operational relevance while ensuring human contact to build customer trust. The approach involved early intervention, combining psychological and physical care. Future plans include refining models and using AI for case handling. Holm emphasised the need for industry standards for preventive impact and highlighted the Nordic model's success in integrating labour market policies, health systems and pension security.



CAMILLA HOLM

‘What really helped us was bringing those two worlds together – the modelling team and the health professionals with customer contact

What specific customer need triggered your focus on prevention-and what decisions did you make that truly moved the needle?

‘It actually started with a series of observations. When we meet customers who are on long-term sick leave, we often see that we already had contact with them earlier. Once they are on sick leave, and it becomes long-term sick leave, then it is too late to prevent. We saw a clear need to start the preventive initiatives earlier. The big shift came when we decided to be proactive and try to prevent customers from becoming sick to the point where they risk long-term absence. Once they are in that position, it is very difficult for us to help them back to work. That decision to act and to invest resources and time earlier was what really moved the needle.’

In terms of impact, which two or three initiatives have had the strongest effect on preventing long-term sickness?

‘The key was using data and combining it with the expertise of our health professionals. We brought together the health team, which helps customers every day and the data scientists who were doing the modelling. When the data was combined with the actual experience from meeting customers and understanding what made them ill and what helped them return to work faster, that’s when things really changed. You can imagine the data scientists working with limited direct customer contact. What really helped us was bringing those two worlds together – the modelling team and the health professionals with customer contact.’

Mental health as a game changer: what have you done differently in recent years-and which specific offerings/programs have delivered the greatest preventive impact and shorter case durations?

‘In recent years, PFA has fundamentally redesigned our prevention approach — especially within mental health — by moving interventions earlier in the disease pathway and by systematically using AI-driven risk prediction to identify individuals before they develop long-term conditions.

PFA uses an AI model that calculates individual risk scores based on health insurance data, treatment history, demographics, geography, and behavioural patterns. This model identifies customers at the highest risk of developing long-term illness, including those with early mental-health-related stress or strain reactions. PFA uses data to ensure customers receive ‘the right treatment at the first attempt,’ which shortens especially mental-health-related and musculoskeletal cases — conditions that typically risk becoming long-term.

This is the program with the clearest and most significant preventive impact:

- 70% reduction in risk of long-term illness (TAE) among contacted customers.
- 54 avoided cases of long-term sickness.
- Significant positive implications for the customers and their close relatives.
- Approx. DKK 86 million in economic benefits for customers.
- More than 4,400 customers contacted and 100+ proactive calls every month. >

The model doesn't 'label' people

We use targeted individual interventions rather than mass screening. PFA does not screen all customers. Only people who already have an established relationship through a previous treatment pathway are contacted – ensuring legitimacy, relevance and higher impact.’

Of course, you have the data, but you need a business case. Which few metrics do you use to manage and communicate impact? And how do you handle lag effects and causal uncertainty when the board asks ‘How do you know that A caused B, and why should we invest in this?’

‘That is exactly the difficult part. First, we focused on operational relevance. We looked at how many customers we reach, how many accept a dialogue with us, and whether the health professionals find the data meaningful. You need to establish trust between the health professionals and the data team.

Second: we track customer feedback – both structured feedback and written comments – because prevention only works if customers perceive it as supportive and relevant.
Third: we’ve done a statistical effect evaluation using a recognised causal approach, Targeted Maximum Likelihood Estimation, to estimate the impact on long-term sickness risk. Based on that, we see a strong preventive effect – around a 70% reduction in the risk of becoming long-term sick in the following year for the customers who receive early support.
We did extensive modelling, where data scientists mapped statistical effects using causal

approaches like targeted maximum likelihood estimation and other robust, data-driven analyses.

Specifically on lag effects and causal uncertainty: prevention has two built-in challenges: lag and causality. The benefit often comes later – because the success is that a long-term illness doesn’t develop – and many outside factors influence sick leave. So we’re careful not to overinterpret quick signals or simple comparisons. We manage this with leading indicators like customer acceptance and professional assessment, and lagging indicators where we track long-term outcomes over time. On causality, we’ve used a recognised causal evaluation approach.

The key for us is to be transparent about what we know and what we’re still learning. We designed it to be supportive and non-stigmatising. The model doesn’t ‘label’ people. It helps us prioritise who might benefit from early intervention and an offer of help. And the outreach is framed as exactly that – an offer of a health guide.

We use only the data we already have about the customer, including basic demographics and their interaction with the health insurance. We also focus on transparency internally – our health professionals need to trust the approach, understand what it is and what it is not, and feel confident that it supports their professional judgement. It is always the human that decides.

What worked best for adoption was building it together: close collaboration between AI and health professionals, plus an ongoing feedback loop from the people doing the outreach calls.’ >

‘ In Denmark, we have a tradition where the insurance product is also provided by the pension company

How do you identify needs early in a fair and non-stigmatising way – and what has worked best to bring employees and managers on board with confidence? Is it a big concern?

‘Yes, because trust operates on several levels. Inside PFA, my colleagues in the health team need to trust the data from the data science team. They are the ones picking up the phone and calling customers, so they must believe that the risk signals are meaningful. With customers and companies, managers and HR departments have to accept that PFA is reaching out to their employees and giving them what we call a ‘we care’ call.

Let me give an example of what happens in practice. Our data shows that risk often builds up over time. Say I first use my health insurance to see a physiotherapist because I have a sore neck. Two months later, I contact PFA again because I would like psychological counselling. At the same time, we can see in the data that I have also moved home recently, which is stressful for most people. When these factors combine, the model raises an alert that this customer may be at risk of becoming long-term ill or long-term sick.

We made sure the modelling reflected what our health professionals actually see in practice. That’s why bringing the two teams together was so important. It is quite uncomfortable for a health professional to call a customer if it turns out to be a false alarm. The way we manage the call is therefore crucial. We typically say something like: ‘We can see you have used your insurance. Did it help you? Were you satisfied with the treatment?’ From there, we explore whether additional support might help.

Once the health professionals felt safe about the data, they could see they were actually helping customers more effectively, because we reach them early. Sometimes we speak with customers before they are themselves aware that they are heading into a stressful situation. The second trust dimension is getting permission from HR departments for these calls. At first, they were sceptical and worried that employees would feel surveilled. But as they saw the benefits, supported by our data and modelling, they realised this helps the individual employee, the company, and society overall by preventing long-term illness. It has taken several years to build this level of trust, and when we measure customer satisfaction on this service it is sky high.’

In terms of products, how do you create coherence between health, work ability, and pension so that employees, employers, and PFA all win-and where have you seen the greatest synergy gains?

‘In Denmark, we have a tradition where the insurance product is also provided by the pension company. So your pension scheme typically includes a health insurance component. As you can tell from this experience, it is very important for us to have data about how customers use their health insurance and link that to their loss-of-work-ability coverage. The Danish term is ‘TAE,’ which stands for loss of ability to work.

So, you have your pension with us, and attached to that you have coverage that pays out if you lose your ability to work, for example if you are injured or become ill in a way that prevents you from working. That product, together with the health insurance, lets us collect data on both >

‘What really matters is that actuaries do not just look at the figures.’

sides and link them. By doing this, we can prevent many customers from becoming long-term sick. For customers and their employers, long-term sickness is a huge cost, so the integrated product setup allows us to serve all parties better.’

What are your leadership principles for the responsible use of data – and especially AI – so that you have enough guardrails, bias testing, explainability, governance, and so on, to ensure fairness and trust? How do you work with that in practice?

‘We have a clear framework, and in practice it comes down to a few important focus areas. We only use data to create value for customers. One key trust issue early on was that customers feared we would use data for pricing or even for excluding some customers. That never happens. Data is only used to help customers. Of course, it also helps PFA because we prevent costly long-term sickness, but the starting point is always customer value.’

We are also very transparent about how we use digital solutions and data, and it is important that customers understand what we do and why. We always ensure human contact and individual assessment. There is always a human being involved. When we reach out to a customer based on data, it is always a person making that contact. That human touch is essential. We maintain strong data quality and use only internal data. For example, we use data on how customers use their health insurance, and we do not bring in random external data sources.’

Turning to the actuaries’ role and expectations: which competencies and mindsets do you especially expect from actuaries? Where have actuaries contributed the most, and what is their ‘secret sauce’?

‘In this specific case, the predictive model was built by our AI team with data scientists, not by the actuaries. However, the actuaries have played a very important role around the model. They use the data in our pricing models and bookkeeping, and they work closely with the AI team to measure effects and integrate the findings into the financial results.’

What really matters is that they do not just look at the figures. The real impact came when the AI team and the health professionals worked together to validate that what the model shows reflects what we see in real life. For example, we looked closely at the indicators of entering a stress-related situation. Actuaries help evaluate what the effect on customers is and how it translates into long-term financial impact and PFA’s bottom line. We are getting better at ensuring that it is not only about the data model, but also about its real effect on customers.’

Do you see a need for industry standards for measuring preventive impact? And what would you concretely invite the actuarial community to own?

‘We clearly see a need for industry standards for measuring preventive impact. It is important to have comparable metrics and robust causal methods that everyone can rely on. We would encourage the actuarial community to lead the >

‘What works in the Nordic model, is the seamless integration of labour market policy, health systems and pension security

development of unified outcome measures, particularly for duration of sickness, level of function, and return to work. Shared standards for causal evaluation and model governance would allow actuaries to raise the bar for the entire industry.

I know this is not easy. But if we could take our experience and models and apply them in the public health system, we could help many more people. We face a lack of labour force, and many people struggle with mental health and other challenges. Standardisation could help society as a whole.’

You mentioned the Danish – or Nordic – model of integration and the labour market. What can other countries learn from this? And where might they run into difficulties?

‘That is a big question. What works in the Nordic model, and in Denmark, is the seamless integration of labour market policy, health systems and pension security. We have a very secure pension model, which is extremely important to Danes, both for long-term financial safety and wellbeing after they leave the labour market, and for short-term security if they become ill.

The core strengths are universal welfare services, coordinated labour market institutions, high levels of trust, and a strong social insurance system. Using modelling in such a system is heavily dependent on trust, and our society is built on that trust. We aim to keep people attached to the labour market while maintaining

income security, which also creates incentives to stay in work.

Where replication often fails is in assuming these results arise purely from specific policies. In reality, the Nordic model depends on high social trust, organised social partners, coordinated wage setting, high taxation to finance universal benefits, and a long tradition of consensus-based governance. All of these surrounding factors make the model work. They are not easy to copy quickly, but they are central lessons that can, at least in part, be exported from the Nordics.’

Finally, PFA’s next strategic steps: where will you focus over the next 12–24 months, and what will success look like?

‘We are continuously refining our modelling to become even more precise. So far, our main actions have been in the psychological area, especially stress, but there is also a lot to be done on the physical health side. Our documentation shows that early, proactive intervention is what prevents long-term illness, so we will increasingly focus on physical conditions as well, again combining real-world experience with what the data tells us.

We are also using AI and modelling to become more efficient in case handling – for example, by using AI to interpret large volumes of legal material, where sometimes you have to read thousands of pages. In prevention, our goal is clear: to extend this early, proactive approach across more areas of our customers’ health so that we reduce the incidence of long-term illness.’ <

DISABILITY INSURANCE

NEW STUDY BY MUNICH RE LEADS TO IMPROVED RISK ASSESSMENT

BY **ALBAN SENN, MATHIAS ORBAN** AND **MARVIN SCHNELLER**

In disability insurance, the stricter the benefit triggers, the lower the risk of losses and the price of the cover. But what about any medical risk loadings? Should these automatically be more favourable for products with stricter benefit triggers? Munich Re's new recommendation is that they should not.

As a leading reinsurer, Munich Re offers medical underwriting guidelines for disability insurance products in over 120 markets. The core products in this type of business include policies for protecting employees from loss of income. In the German market, these include occupational disability insurance and work incapacity insurance. A look at the benefit triggers illustrates the differences: In the case of income protection insurance, in Germany, the claim occurs when the insured individual can perform less than 50% of their last occupation for a period of at least six months. Total and permanent disability insurance has a stricter definition of benefit triggers and operates only if the insured is no longer able to perform any kind of work on a permanent basis.

THE CHALLENGE

But what about the loadings for risk-relevant pre-existing conditions for occupational disability and total and permanent disability insurance? Given the different product definitions, do these

conditions have a different impact on the risk of losses, resulting in a need to adjust medical loadings either upward or downward? If so, for which pre-existing conditions are the product-related relative risk differences most significant? Data-driven answers to these questions have been lacking, with the result that medical underwriting guidelines in this area have so far been developed primarily based on expert assessments.

There has been a lack of usable data and analyses for determining risk relations and an evidence-based assessment. The reasons for this are complex. Medical literature rarely addresses such specific insurance-related medical issues, as medical research primarily focuses on treatment-relevant outcomes rather than findings aimed at refining insurance definitions. In addition, the data from the private insurance industry does not usually provide any detailed medical information – for example on different durations of incapacity to work due to illness – for data protection reasons alone. >

THE STUDY DESIGN

In order to increase the accuracy and consistency of risk assessment across all types of disability insurance products, Munich Re's Medical Research & Development team used alternative data sources and developed these as part of its own study. This was made possible by the combination of actuarial and insurance-medicine expertise, as well as the company's own portfolio data and additional external health insurance data with information on several million insured individuals.

The team conducted a retrospective longitudinal study and investigated the connection between diagnosed pre-existing conditions and subsequent sick leave or periods of reduced earning capacity. A period of eight years was looked at. The dataset contained diagnoses in ICD-10 format, demographic data in the form of six age bands, and socioeconomic information.

In terms of measurable parameters, the study analysed periods of incapacity to work of 4, 13 or 26 weeks as indicators for triggering disability or occupational disability insurance, and the receipt of a reduced earning capacity pension as an indicator for triggering total and permanent disability insurance.

To obtain representative data for risk assessment in the specified disability insurance products, the project team first cleaned the initial dataset. Only data from insured individuals in the product-relevant age range who are able to pursue gainful employment and are eligible for disability insurance were analysed. The relative risks for various pre-existing conditions were then determined and corresponding risk loadings calculated. To rule out confounding and interaction effects, the team then adjusted the results using multivariate analyses and actuarial expertise. >

FIGURE 1: Many pre-existing conditions lead to short-term absence from work, while a few pre-existing conditions lead to longer absences from work

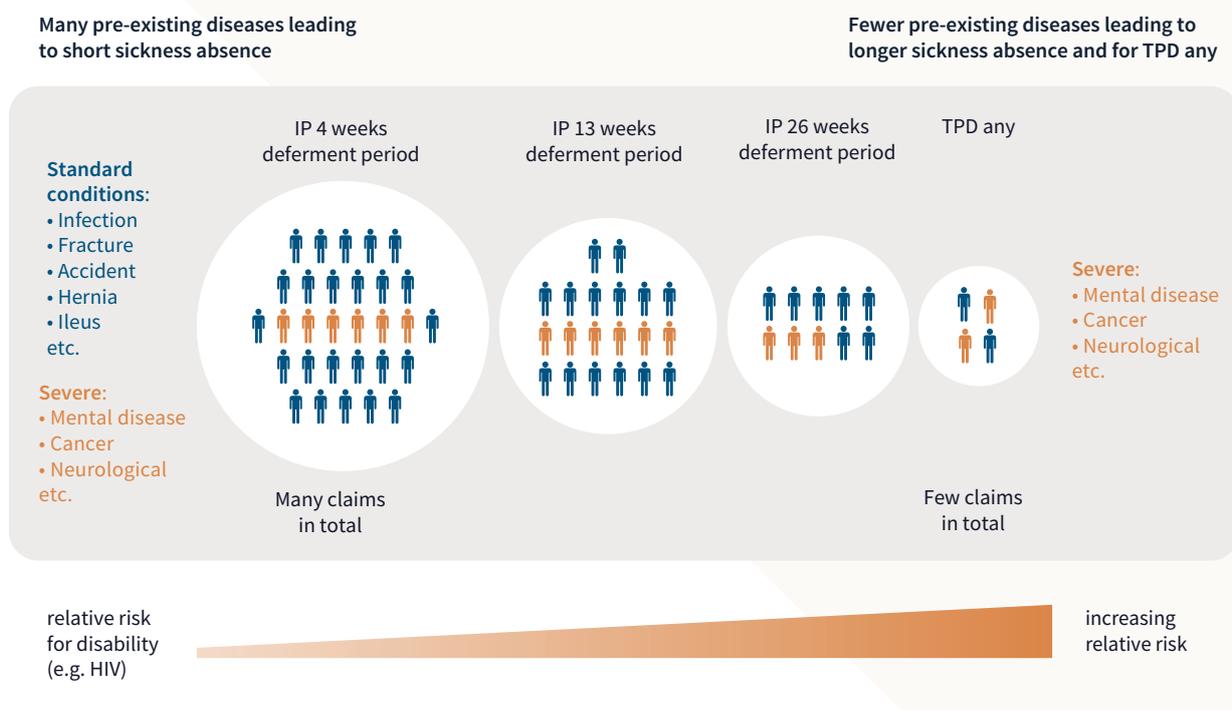
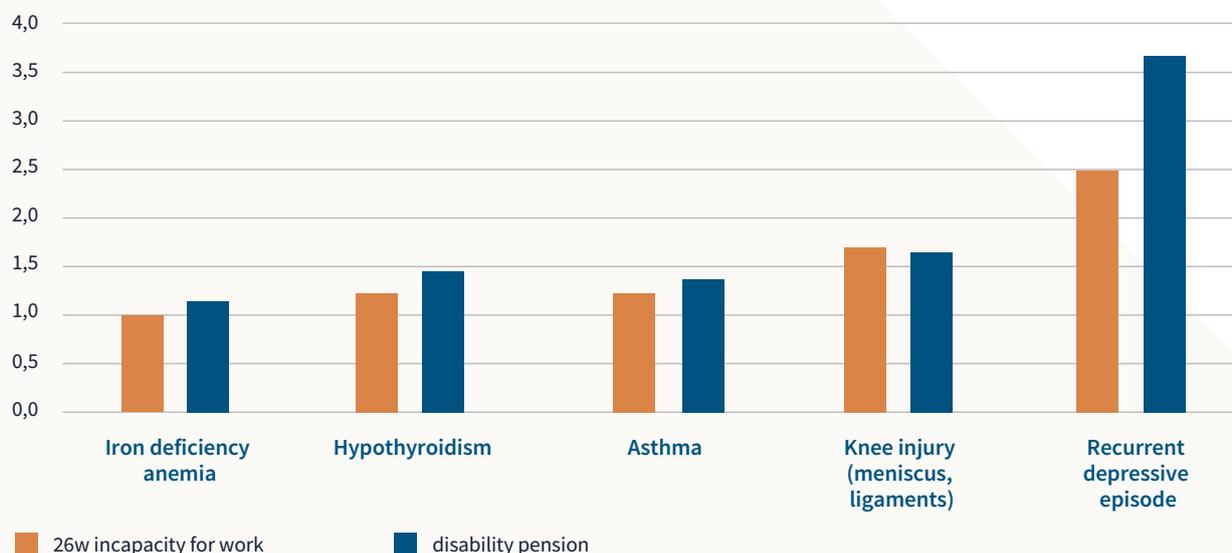


FIGURE 2: The relative risks of work incapacity and disability vary according to the severity of the underlying condition

Relative risk for 26 weeks of incapacity for work and disability pension



Two patterns:

Pre-existing conditions can either have a **stable relative risk** in incapacity for work **and** disability pension or show an **increase in relative risk** from incapacity for work to disability pension.

Relative risks depend on the severity of the pre-existing condition (AU = incapacity for work; EMR = reduced earning capacity pension).

NEW FINDINGS

The study confirms a fundamental actuarial assumption: work incapacity insurance with strict benefit definitions results in fewer claims compared to more complex products with lower-threshold benefit triggers. However, several findings are new and, in some cases, surprising. The study examined over 1,000 medical diagnoses in ICD-10 format, revealing that while many illnesses cause short-term work absences during the insurance period, only a small number lead to longer-term absences. (Figure 1)

Another finding is particularly relevant for evidence-based risk assessment. Contrary to what is generally assumed, the relative risk associated with individual pre-existing conditions is not homogeneous across the

product groups (Figure 2). On the contrary: for products with stricter benefit triggers in particular, individual serious or chronic illnesses such as cancer, heart disease, serious neurological and mental disorders have an increased risk and lead to a disproportionately high number of claims.

The increasing risk patterns can be seen in people with coronary heart disease, for example. In these individuals, the risk of a claim is increased by 100% for products with a short deferment period. For products with a reduced earning capacity pension, the risk increases to up to 300%. These increases reflect the higher susceptibility of the stricter benefit trigger to serious outcomes of illness. >

CONCLUSIONS

The study shows that illnesses with milder or easily controllable clinical courses exhibit stable risk patterns across the disability insurance product lines. The medical risk loadings for such illnesses can therefore be applied uniformly to all product types. However, there is a group of severe or chronic illnesses which, with stricter definitions of disability, have a higher relative risk and thus increasing risk patterns.

A look at the stability of entire portfolios shows how relevant these findings are. The fact is that for favourable coverages with a strict definition of benefits, every additional claim due to pre-existing conditions carries more weight. This

makes it all the more important to calculate loadings in line with the risk involved. This is because loadings that are too low and not risk-adequate can jeopardise the stability of entire insurance portfolios if the latter contain many high-risk contracts. The risk loadings should therefore not automatically be low just because the chosen disability product is simple and inexpensive.

Munich Re has already implemented the findings and revised its underwriting guidelines accordingly. Insurers are now in a position to assess disability risks more precisely, make risk-adequate decisions to protect the community of policyholders, and write sustainable business. <



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UNRAVELLING PAST TRENDS

IN SOCIO-ECONOMIC LONGEVITY INEQUALITIES

BY **FANNY JANSSEN**

In my previous research, I have demonstrated the added value for mortality forecasting of a detailed understanding of past trends, and of separately projecting non-linear trends in lifestyle-attributable mortality (such as smoking-attributable mortality) next to the more linear trends in non-lifestyle-attributable mortality. Similarly, I argue that a better understanding of past trends in socio-economic mortality inequalities and its different components is essential for an accurate forecast of future socio-economic inequalities in longevity. As the first part of the '*Future Longevity Inequalities*' research project, my research team and I have examined the individual and combined impact of smoking, alcohol, and obesity on past trends in educational inequalities in life expectancy in England & Wales, Finland and Italy.



EXPECTED IMPORTANT ROLE OF LIFESTYLE FACTORS

In modern welfare states, people in a disadvantaged socio-economic position (SEP), either measured by income, occupation, or education, live on average 3-10 years less than people in an advantaged SEP. Those with lower SEP generally have worse opportunities to avoid premature death. They generally have higher risks of material deprivation (e.g. inadequate housing), higher risks of unemployment and – related - psychosocial stress, worse health behaviours, and more limited access to quality health care.

In recent decades, these unjust and undesirable socioeconomic inequalities in mortality and life expectancy have even widened in several European countries despite efforts to reduce them. This increase has puzzled researchers in the field of socio-economic health inequalities, and has raised concerns about how these inequalities will develop in the future. To fully grasp the past trends in socio-economic mortality inequalities, and to accurately predict them into the future, it is essential to examine potential trend breaks and to assess the role of lifestyle factors.

Smoking, alcohol misuse, and behaviours resulting in obesity (unhealthy diets, insufficient physical activity) are likely determinants of past trends in socio-economic inequalities in life expectancy. First, they are important preventable risk factors of mortality in Europe, whose prevalence and associated mortality are currently higher among people with low SEP compared to those with high SEP. Consequently, these lifestyle factors are known to importantly contribute to socioeconomic mortality inequalities in high-income countries. Second, smoking, alcohol misuse, and obesity have strong effects on trends in national life expectancy, as these lifestyle factors typically develop over time as wave-

shaped epidemics, with their prevalence and associated mortality increasing strongly and then (eventually) declining. Third, the timing and the impact of these lifestyle ‘epidemics’ differ between socio-economic groups. Smoking, obesity, and alcohol ‘epidemics’ occurred relatively late among those with a less advantaged SEP, but with larger effects.

TRENDS IN EDUCATIONAL INEQUALITIES IN LIFE EXPECTANCY

For England & Wales (1972-2017), Finland (1971-2017), and Italy (Turin, 1972-2019), several phases and breakpoints in the trends in educational inequalities in remaining life expectancy at age 30 (e30) can be observed. See Figure 1 for the trends since around 1990. Whereas long-term decreases in educational inequalities in e30 occurred among Italian women (1972-2003), and among British males (1972-2008) and British females (1992-2017), long-term increases occurred among Finnish males (1982-2008), Finnish females (1985-2017) and Italian males (1976-2018). Among males, clear recent reversals in the trends occurred. British males exhibited a reversal from decreasing to increasing inequality around 2006-2008, Finnish males experienced a reversal from increasing to decreasing inequality around 2008.

The long-term increases (Finnish males 1982-2008; Finnish females 1985-2017; Italian males 1976-2018) were driven by faster mortality declines among the highly-educated aged 65-84, and by mortality increases among the low-educated aged 30-59. The long-term decreases among British males (1976-2008) and Italian females (1972-2003) were driven by faster mortality improvements among the low-educated than among the high-educated at age 65+. The recent reversals were driven by mortality trend changes among the low-educated aged 30-54. >

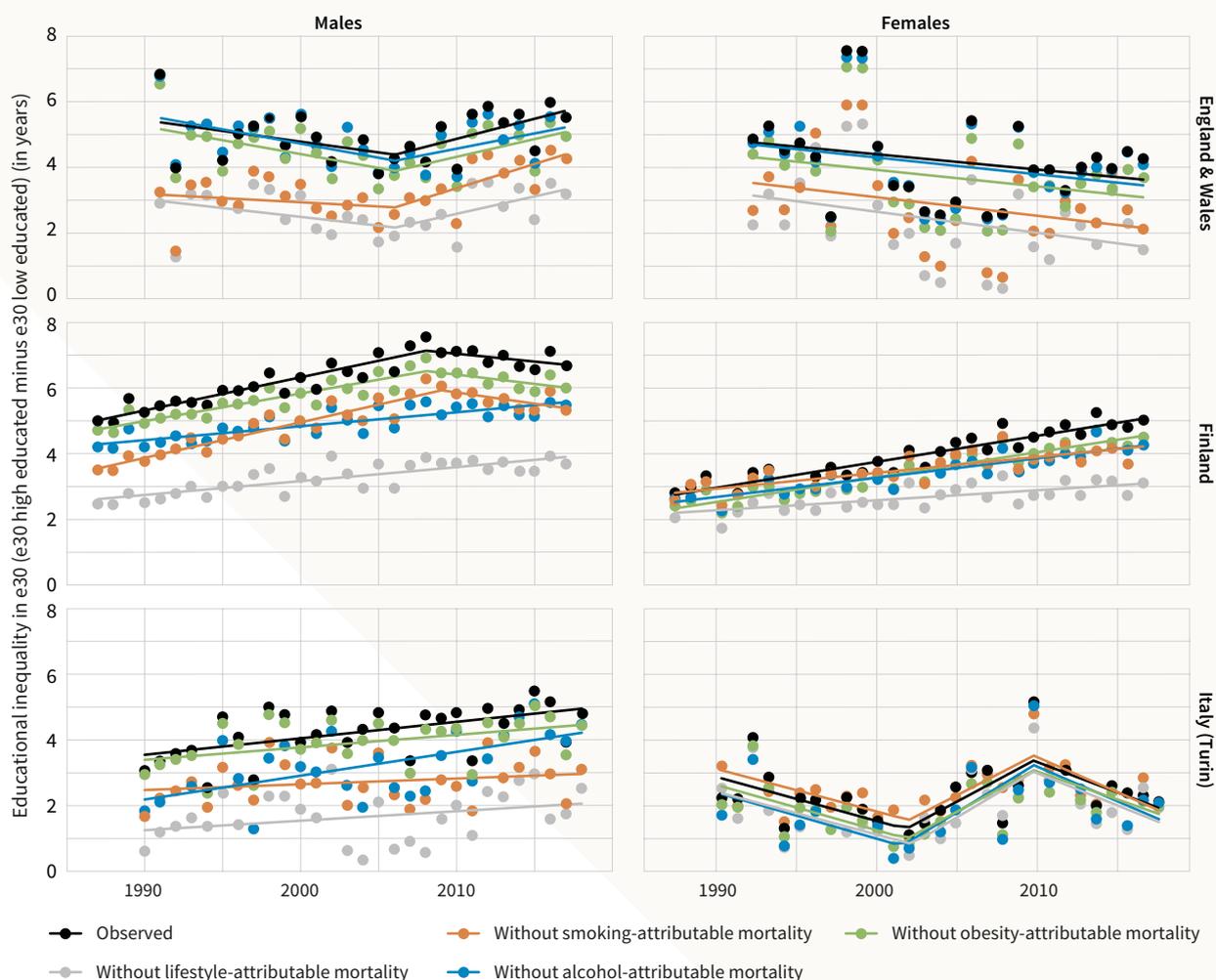
THE ROLE OF LIFESTYLE FACTORS ON TRENDS IN EDUCATIONAL INEQUALITIES IN E30

Figure 1 illustrates that smoking, alcohol, and obesity not only play a significant role in explaining the levels of educational inequalities in e30, but also in explaining the secular trends in educational inequalities in e30. That is, without mortality due to smoking, alcohol, and obesity

(hereafter referred to as 'lifestyle-attributable mortality'), educational inequalities in e30 are considerably lower, and trends in educational inequalities in e30 are quite different.

For Finnish males, the reversal from increasing to declining educational inequalities in e30 in 2008 disappears upon removing 'lifestyle-attributable mortality' and alcohol-attributable mortality >

FIGURE 1 Time trends in educational inequalities in remaining life expectancy at age 30 (e30) with and without smoking-, alcohol-, and obesity-attributable mortality (individual and combined), by sex and country. England & Wales (1991-2017 males; 1992-2017 females), Finland 1987-2017, Italy (Turin) 1990-2018.



Source data: ONS Longitudinal Study, Statistics Finland & Turin Longitudinal Study

Dots represent the observed values; lines represent the fitted values from the segmented regression analysis. 'Lifestyle-attributable mortality' refers to mortality that is attributable to smoking, alcohol, and obesity combined. The high educated are those with tertiary education. The low educated are those with no, pre-primary, primary, and lower secondary education. For females in England & Wales, the segmented regression is performed over the years 1992-2017, because of an outlier in 1991.

Source: Janssen et al. 2025 - Figure S4

(AAM). This can almost entirely be attributed to a similar reversal in trends in educational inequalities in AAM, largely driven by alcohol taxes and prices. Before 2008, increases in AAM occurred particularly among the low- and middle-educated because of reducing alcohol taxes and prices. The introduction of stricter alcohol policies around 2008 resulted mainly in declines among those with the highest level of excessive alcohol consumption: low educated males.

In addition, without ‘lifestyle-attributable mortality’, the observed increases in educational inequalities in e30 were approximately halved not only among Finnish males (1987-2008), but also among Finnish females (1987-2017) and Italian males (1990-2018). Moreover, among British females (1992-2017), the decline in educational inequalities in e30 would have been 38% larger without ‘lifestyle-attributable mortality’. For British males, the trends with and without ‘lifestyle-attributable mortality’ are largely similar.

Next to the increasing educational inequalities in AAM for Finland up to 2008, the population-specific trends in educational inequalities in smoking-attributable mortality (SAM) prove to be important. British (and Finnish) males who are frontrunners in the smoking epidemic, and already exhibited declines in SAM for quite some time, exhibit declining inequalities in SAM due to smaller declines in smoking-attributable mortality among the high educated – who already reached low SAM levels – compared to the low educated. Italian males reached the peak in SAM more recently, albeit later for the low than the high educated, resulting in lower declines for the low educated, and consequently increases in educational inequalities in SAM. Females only exhibited increases in SAM recently, which were stronger for the low educated, particularly among Finnish females, resulting, for them, in increasing educational inequalities in SAM.

Without ‘lifestyle-attributable mortality’, a largely similar, modestly increasing trend for Finnish males and females, and – to a lesser extent – for Italian males and females, can be observed. This modest increase could be the result of gradual increases in general inequalities in material or other social resources, potentially resulting from the lower educated becoming a more homogeneous group with worse health because of educational expansion, or from the increasing inflow of people from low-income countries.

CONCLUSION

The identified trend breaks in educational inequalities in e30 indicate that socio-economic inequalities in longevity are plastic. Smoking, alcohol misuse, and obesity combined proved responsible for the recent reversal in educational inequalities in e30 among Finnish males and proved important determinants of the observed increases in educational inequalities in Finland and among Italian males.

Regarding future trends in socio-economic longevity inequalities, uniform trends in educational inequalities in e30 without ‘lifestyle-attributable mortality’ could provide a strong basis, as these trends likely point to structural determinants that have a more gradual effect. In addition, the highly time-varying social gradient of, particularly, smoking- and alcohol-attributable mortality, should be taken into account, by separate – advanced - projections. Finally, the effects of potential modifying factors should ideally be taken into account; in particular, the effects of preventive health policies for the lifestyle component, and anticipated societal changes for the non-lifestyle component. This will be the goal of the second part of the ‘*Future Longevity Inequalities*’ research project by Fanny Janssen. >

NOTES

Fanny Janssen's work is supported by the Dutch Research Council (NWO) in relation to the research programme 'Forecasting future socio-economic inequalities in longevity: the impact of lifestyle 'epidemics'' under grant no. VI.C.191.019. See www.futurelongevitybyeducation.com.

Socio-economic position (SEP) is operationalised by highest level of completed education.

Education is considered a more stable measure of SEP than occupation and income, because it is not subject to reverse causation problems at higher ages. In addition, education data are available for both males and females and for more countries and longer time periods than data for occupation and income.

Individually linked (cause-specific) mortality data by educational level (low, middle, high) for those aged 30 and over, by five-year age groups and single calendar year were analyzed for England & Wales (E&W), Finland and Italy (Turin). The trends in educational inequalities in remaining life expectancy at age 30 (e30) (e30 high educated minus e30 low educated) were fitted by means of segmented regression to identify trend breaks. Subsequently, the fitted trends in educational

inequalities in e30 were compared with similar trends but then without 'lifestyle-attributable mortality' to assess the role of smoking, alcohol, and obesity combined. 'Lifestyle-attributable mortality' by educational level was estimated by multiplicatively aggregating previous estimates of smoking-, alcohol-, and obesity-attributable mortality by educational level.

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RISK ATTRIBUTION UNDER IFRS 17

STRUCTURAL SEPARABILITY

AND THE INTEGRITY OF
ACTUARIAL NARRATIVES



BY **EYTAN ELLENBERG**

INTRODUCTION: IFRS 17 AND THE CHALLENGE OF CREDIBLE EXPLANATIONS

The implementation of IFRS 17 has significantly raised expectations regarding actuarial explanations. Insurers are no longer assessed solely on the robustness of their estimates, but increasingly on the clarity and credibility of the narratives that accompany movements in insurance contract liabilities. Boards, auditors, and regulators now expect reserve changes to be explained through underlying drivers – typically frequency, severity, and inflation. >

While this shift has improved transparency, it has also revealed a structural tension. The demand for granular attribution often exceeds what the underlying loss data can reliably support. In practice, actuarial teams may feel compelled to present precise decompositions even when the data structure itself does not allow for clear separation of drivers.

This article argues that the integrity of IFRS 17 narratives depends not only on modelling sophistication, but on a prior assessment of whether attribution is *structurally feasible*. It introduces the **Risk Attribution Index (RAI)** as a governance-oriented diagnostic designed to evaluate when loss triangles can legitimately support differentiated explanations – and when they cannot.

ATTRIBUTION PRACTICES AND THEIR IMPLICIT ASSUMPTIONS

Traditional actuarial attribution frameworks rest on an implicit assumption: that frequency, severity, and inflation act as separable forces whose effects can be independently identified in loss development data. When this assumption holds, attribution is not only possible but informative.

Conceptually, each driver is expected to leave a distinct statistical signature:

- Frequency changes manifest across accident years.
- Severity changes appear as level shifts within development.
- Inflation introduces systematic calendar-year effects.

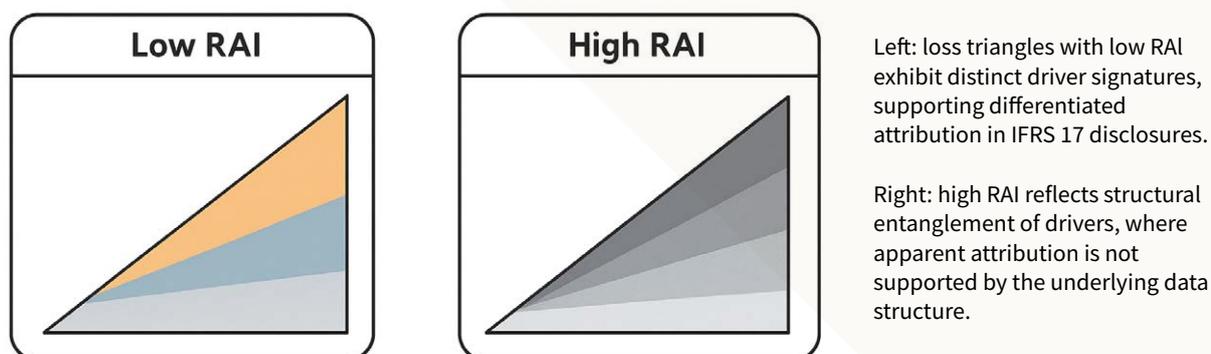
In idealised data, these signatures are sufficiently distinct to permit meaningful decomposition. However, real-world insurance portfolios rarely behave in such a clean manner. Economic shocks, operational responses, and claims management practices often cause multiple drivers to move simultaneously, blurring these distinctions.

When the underlying assumption of separability fails, attribution does not merely become less precise – it becomes structurally unreliable.

STRUCTURAL ENTANGLEMENT AND MASKED DYNAMICS

Periods of economic stress illustrate this problem clearly. Inflationary environments may simultaneously increase claim sizes, delay settlements, and alter reporting patterns. Supply-chain disruptions can affect both the cost and >

FIGURE 1: Structural separability and IFRS 17 narrative integrity



timing of claims. Management actions taken to mitigate one risk may inadvertently amplify another.

These interactions produce what can be described as **structural entanglement**: a condition in which different causal mechanisms generate similar statistical patterns in the data. The result is *masked dynamics* – situations where underlying drivers are present but indistinguishable from one another.

From a governance perspective, the principal risk is not uncertainty itself, but false precision. Attribution outputs may appear authoritative, complete with clean percentages and reconciliations, while offering little insight into the true causal structure of reserve movements. Such narratives can be difficult to defend when challenged by auditors or supervisors.

THE RISK ATTRIBUTION INDEX AS A STRUCTURAL DIAGNOSTIC

The Risk Attribution Index (RAI) is designed to address this issue by shifting the focus from *how* to attribute, to *whether attribution is structurally justified at all*. RAI evaluates the degree to which loss triangle data contain sufficient independent information to distinguish frequency, severity, and inflation effects.

- **Low RAI** values indicate that driver signatures are sufficiently distinct to support differentiated attribution.
- **High RAI** values signal strong structural overlap, where drivers move together and separation becomes unreliable.

Crucially, RAI is **not** a reserving method, a performance metric, or a regulatory requirement. It does not replace existing actuarial techniques, nor does it prescribe a particular modelling approach. Instead, it

functions as a **governance-oriented diagnostic**, supporting professional judgement by highlighting structural limitations in the data.

In this sense, RAI serves as a safeguard: it helps actuaries recognise when attribution narratives risk exceeding what the data can legitimately support.

IFRS 17 DISCLOSURES AND NARRATIVE INTEGRITY

IFRS 17 emphasises transparency and faithful representation. Paragraphs such as IFRS 17 §103 highlight the importance of explaining changes in insurance liabilities in a manner that is both meaningful and comprehensible. However, the standard does not mandate a specific level of attribution granularity.

When loss triangles exhibit high structural entanglement, forcing a detailed decomposition may undermine the integrity of disclosures. Presenting highly granular explanations in such cases can create a misleading impression of certainty, exposing insurers to credibility risks during audit or supervisory review.

Conversely, acknowledging structural limitations and adopting scenario-based explanations may better align with the spirit of IFRS 17. Such narratives reflect professional judgement and demonstrate an understanding of the underlying data constraints, rather than an overreliance on mechanical outputs.

PROPORTIONALITY AND THE EUROPEAN GOVERNANCE CONTEXT

Proportionality is a cornerstone of European actuarial practice and regulation. Tools such as RAI align naturally with this principle by supporting judgement rather than enforcing rigid methodologies. >

In a European governance context, RAI can facilitate dialogue between actuarial, finance, risk, and audit functions. Rather than acting as a binary test, it provides a shared framework for discussing whether additional narrative detail enhances understanding or risks obscuring it.

Importantly, RAI does not dictate outcomes. It informs governance discussions by clarifying when attribution is structurally plausible and when restraint is warranted. Used in this way, it supports consistent documentation of professional judgement within existing control frameworks.

PRACTICAL IMPLICATIONS FOR INSURERS

European insurers may consider integrating structural diagnostics such as RAI into their IFRS 17 processes through several practical steps:

- Routine assessment of separability during reporting cycles, particularly following significant environmental or operational changes.
- Escalation of high-RAI findings to governance forums, ensuring alignment on disclosure strategy.
- Use of scenario-based narratives when attribution is structurally fragile, accompanied by clear explanation of limitations.

- Documentation of judgement, demonstrating that narrative choices reflect data structure rather than convenience.

These practices reinforce transparency without imposing new methodological burdens, and they enhance the credibility of actuarial communication across stakeholder groups.

CONCLUSION: PROTECTING TRUST THROUGH DISCIPLINED JUDGEMENT

IFRS 17 has heightened scrutiny of actuarial narratives. Meeting these expectations requires more than technical competence; it demands disciplined judgement about what loss data can – and cannot – credibly explain.

By highlighting structural separability, the Risk Attribution Index provides a pragmatic way to assess the integrity of attribution narratives before they are presented to stakeholders. It does not seek to replace existing tools, but to ensure that explanations remain aligned with the informational limits of the data.

In an environment where trust and transparency are paramount, recognising when not to over-interpret loss triangles may be one of the most valuable contributions actuaries can make to effective governance. <



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RISK MITIGATION ACCOUNTING: A NEW PORTFOLIO- BASED MODEL UNDER CONSULTATION

BY **PIERRE THÉRON** AND **PIERRE BOUTONNET**

In December 2025, the International Accounting Standards Board (IASB) published an Exposure Draft proposing amendments to IFRS 9 Financial Instruments and IFRS 7. The proposal introduces an optional Risk Mitigation Accounting (RMA) model intended to better represent in financial statements the economic effect of managing repricing risk on a net basis. The consultation is open until 31 July 2026.

CONCEPT AND ARCHITECTURE OF THE RMA MODEL

The proposed Risk Mitigation Accounting model aims to provide an accounting representation of a central activity of many financial institutions: the mitigation, on a net basis, of repricing risk at portfolio level. Repricing risk is defined as a type of interest rate risk arising from differences in the timing and amount of financial instruments that reprice to benchmark interest rates. In practice, banks and insurers frequently manage this risk dynamically by aggregating exposures across portfolios of financial assets, financial liabilities and certain future transactions, rather than managing risk instrument by instrument.

The accounting challenge that motivates RMA stems from measurement asymmetry. Interest rate derivatives used to mitigate repricing risk are measured at fair value through profit or loss. By contrast, many items included in underlying portfolios – such as fixed-rate assets and liabilities

measured at amortised cost – do not reflect changes in market rates in profit or loss on the same basis. As a result, earnings volatility may largely reflect the fair value remeasurement of swaps, even when repricing risk has been mitigated at a net level.

The RMA model replaces an instrument-by-instrument hedging logic with a portfolio-based framework structured around risk management concepts defined in the Exposure Draft.

The key elements are:

- the **net repricing risk exposure**, determined by aggregating underlying portfolios into repricing time bands based on expected repricing dates;
- a formally specified **risk mitigation objective**, expressed as an absolute amount of repricing risk to be mitigated and capped at the net repricing risk exposure in each time band; >

- the construction of **benchmark derivatives**, theoretical instruments that replicate the timing and amount of repricing risk specified in the risk mitigation objective; and
- the recognition of a **risk mitigation adjustment** in the statement of financial position.

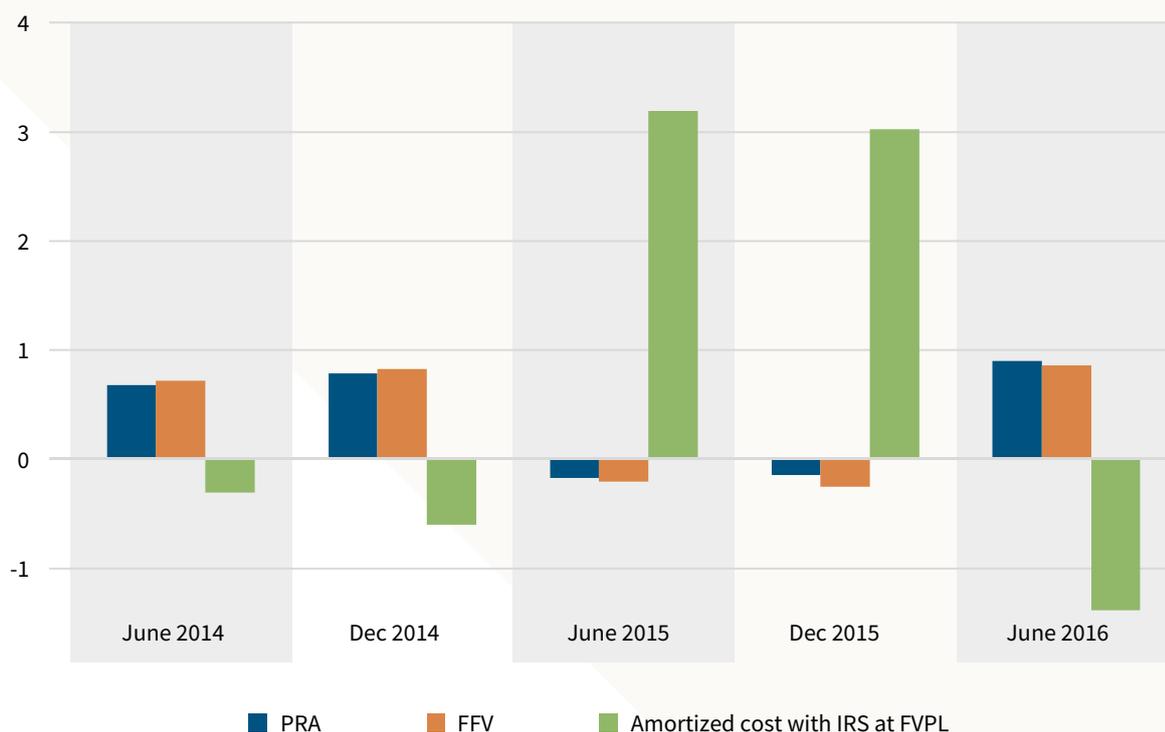
This architecture aims to ensure that financial statements represent the extent to which an entity's risk management activities have successfully mitigated repricing risk, while remaining aligned with how repricing risk is managed internally.

ACCOUNTING MECHANICS: FROM ASYMMETRY TO PORTFOLIO VIEW

To illustrate the issue addressed by RMA, consider a simplified case: fixed-rate assets funded by floating-rate liabilities, with an interest rate swap used to mitigate repricing risk on a net basis. Suppose the reference floating rate first decreases and then increases.

Under a traditional accounting configuration – balance sheet largely measured at amortised cost and swap measured at fair value through profit or loss – earnings volatility is primarily driven by changes in the fair value of the swap. The underlying balance sheet items that generate repricing risk do not produce offsetting profit >

FIGURE 1: Earnings volatility under different accounting



The green bar corresponds to a configuration where underlying portfolios remain at amortised cost and designated derivatives are measured at fair value through profit or loss. Earnings are highly volatile.

The orange bar illustrates a broader fair value perspective, where rate-sensitive balance sheet items are also remeasured, producing offsetting effects.

The blue bar represents a portfolio-based view consistent with the RMA logic, where the accounting representation is structured around net repricing risk exposure and the risk mitigation objective. Volatility is reduced because the accounting outcome reflects mitigation at an aggregate level rather than standalone derivative fair value changes.

or loss effects at the same time. The resulting volatility reflects accounting mismatch rather than pure economic exposure.

A broader fair value approach would reduce this asymmetry, but would not necessarily reflect how repricing risk is managed in practice.

The RMA approach introduces a portfolio-based representation aligned with dynamic risk management.

Under the proposed model, the measurement of financial instruments in underlying portfolios remains unchanged, and derivatives continue to be measured at fair value through profit or loss. However, a **risk mitigation adjustment** is recognised in the statement of financial position. This adjustment is measured as the lower of:

- the cumulative gain or loss on designated derivatives; and
- the cumulative change in the fair value (present value) of benchmark derivatives.

The accumulated risk mitigation adjustment is subsequently recognised in profit or loss in the same periods in which repricing differences arising from underlying portfolios affect profit or loss. If the accumulated adjustment exceeds the present value of the net repricing risk exposure, the excess must be recognised immediately in profit or loss and cannot be reversed.

The model therefore defers part of the derivative fair value changes so that profit or loss better reflects the timing of repricing effects in the underlying portfolios.

IMPLICATIONS FOR INSURERS

Although most current users of IAS 39 macro hedge accounting are banks, the Exposure Draft explicitly raises questions for entities that issue insurance contracts under IFRS 17. The IASB seeks feedback on whether insurance contract assets and liabilities – assuming they are eligible for inclusion in underlying portfolios – could be incorporated into the RMA framework, and whether doing so would better represent the economic effect of insurers' interest rate risk management activities.

For actuaries, this is a key point. Insurers frequently manage assets and insurance liabilities jointly from both an earnings perspective and an economic value perspective. The interaction between IFRS 17 measurement (including discount rate effects and the contractual service margin) and a potential RMA adjustment raises conceptual and operational questions. The IASB is therefore inviting specific input on the alignment between insurers' risk management strategies and the characteristics required to apply RMA.

CONCLUSION

The proposed Risk Mitigation Accounting model does not change how financial instruments or derivatives are measured. Instead, it reframes how derivative fair value changes are reflected in profit or loss when repricing risk is managed dynamically and on a net basis.

By anchoring the accounting representation in the net repricing risk exposure and the risk mitigation objective, the IASB seeks to align financial reporting more closely with risk management practices, enhance transparency, and reduce reliance on proxy hedging techniques. <



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COLUMN

HEALTH DATA, ACTUARIAL FAIRNESS AND THE HIDDEN RISK OF DISCRIMINATION IN INSURANCE PRICING

The use of health data in actuarial pricing is increasingly situated at the intersection of technical necessity and societal expectations. Insurers must rely on accurate data to assess and price risks appropriately, while regulators and consumer organisations remain alert to issues of fairness, potential discrimination and unequal access to insurance. As health information becomes more digitalised and regulatory frameworks evolve, the challenge of preventing both intentional and unintentional discrimination grows in complexity.

A central theme emphasised by the Actuarial Association of Europe (AAE) is the distinction between legitimate risk differentiation and unlawful discrimination. Actuarial pricing principles rest on the understanding that customers presenting similar levels of risk should be treated consistently. Yet health data contains sensitive variables, some of which cannot be used under legal, ethical or societal constraints. These boundaries require careful navigation to preserve pricing adequacy while ensuring equitable treatment.

Although the debate has increasingly connected to the broader use of AI, the underlying issue predates advanced analytics. Nevertheless, the Geneva Association has correctly noted that AI driven modelling may reveal correlations that appear actuarially relevant but could, in practice, lead to discriminatory outcomes. Such risks include indirect associations with genetic predispositions, environmental factors or socioeconomic signals embedded within health related datasets.

Within the AAE, we did a considerable work a couple of years ago supporting the European Commission and stakeholders in assessing the implications of the European wide Right to Be Forgotten (RTBF). The initiative aimed to allow cancer survivors, after a specified period, to refrain from disclosing previous diagnoses when seeking insurance. While this objective clearly supported improved access, it simultaneously challenged established underwriting structures. The AAE has highlighted how fairness objectives may conflict with existing regulatory frameworks and the practicalities of actuarial risk assessment, underscoring the need for balanced policy design that considers both societal protections and technical feasibility.

The use of AI in health related underwriting introduces additional sources of potential discrimination. Models trained on historical claims and medical data may unintentionally replicate past inequalities or infer sensitive health conditions from indirect variables. These effects are particularly acute for lower income groups, who may already face structural disadvantages. Public concerns over factors such as BMI based underwriting or genetic data further illustrate the complexity of aligning technological developments with consumer trust. Ensuring fairness requires robust governance, transparent modelling and continuous monitoring to prevent health data from reinforcing hidden biases within pricing decisions.

New possibilities of using more health data in insurance pricing must be approached with careful consideration of fairness and regulatory coherence. The RTBF debate illustrates the inherent tension between supporting vulnerable groups and maintaining sustainable risk pooling. As data sources expand and analytical techniques grow more sophisticated, insurers must reinforce governance standards, strengthen transparency and ensure that underwriting decisions remain both technically justified and socially acceptable. Ultimately, maintaining trust in the insurance system requires policies that balance societal expectations with actuarial soundness, safeguarding both consumer protection and market stability.

Lauri Saraste, Chairperson AAE Insurance Committee

COLOPHON

The European Actuary (TEA) is the quarterly magazine about international actuarial developments. TEA is written for European actuaries, financial specialists and board members. It will be released primarily as e-mail newsletter. The views and opinions expressed in TEA are those of the authors and do not necessarily reflect the official policy or position of the Editorial Board and/or the AAE. The Editorial Board welcomes comments and reactions on this edition under info@actuary.eu.

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NEXT ISSUE

The next issue will appear 1 June 2026.

Suggestions can be e-mailed

to info@theeuropeanactuary.org.

The deadline is 1 may 2026.

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