NEXT GENERATION AI-AUGMENTED UNDERWRITING

NOT IF, BUT HOW

Munich RE

Next generation AI-augmented underwriting

"Transform your customer experience, distribution and efficiency while managing risk complexity, powered by domain knowledge, responsible AI, data, modern technology and risk acceptance."

Lee Sarkin, Chief Analytics Officer, APAC, Middle East, Africa (Life & Health), Munich Re

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In today's insurance landscape, providing a seamless, personalised, and digitally enabled customer experience is paramount for meeting customer needs and ultimately sales. Traditional underwriting processes however can be inconvenient, time-consuming, and intrusive, deterring customers and impeding sales. Additionally, insurers are exposed to costly non-disclosure or fraudulent behaviour. Munich Re's artificial intelligence (AI)-augmented underwriting solution is designed to address these challenges. To do so, we combine deep domain knowledge, responsible AI, data, modern technology, and risk acceptance to significantly improve the customer experience, operational efficiency, risk selection, and ultimately sales and profitability for life and health insurers.

Medical and financial underwriting remains an integral part of this customer experience and is deeply ingrained in insurers' operations and legacy systems. It's at the very core of their risk management functions, ensuring long-term profitability and solvency. It's common for insurers to have already established automated underwriting rule engines (UREs). Insurers face real urgency to achieve competitive advantage to overcome sales pressure, yet this requires insurers to balance speed-to-market of improved customer experiences against future claims risk or price competitiveness. Now more than ever, insurers seek to further monetise existing investments in UREs by unlocking the value of data from UREs, back-office systems and external sources to enable the transition to the next generation of underwriting (UW2.0), "Augmenting underwriting with AI", which uses AI/machine learning (ML)/predictive models and modern cloud technology to augment existing underwriting processes. This is nothing short of a revolution in customer experience.

The key to success lies in getting the above balance right which requires insurers to manage a new “risk complexity” arising from the interplay of required capabilities. These range from specialised insurance domain knowledge, developing robust AI models that comply with responsible AI regulations, securing sign off from senior actuarial risk management before AI model deployment on the risks posed to insures’ future claims, integrating real-time AI model predictions into UREs and underwriting processes and safely maintaining AI models in production via machine learning operations (MLOps) technology.
The ability to manage this new risk complexity is now table stakes…but are insurers prepared?

Not surprisingly, advanced analytics/AI has become core to insurers’ digital success strategy. The industry is pivoting from presentations and proof-of-concepts to implementations with demonstrable value for end customers and Munich Re is at the forefront, providing amongst the first live AI deployments in underwriting in Asia, Middle East, and Africa, now live in production for years with demonstrable improvements in insurers’ customer experience. The life and health insurance industry’s progress in monetising AI is at an inflection point.

The shift to digital sales platforms and processes that meet customer expectations is rapidly accelerating exponentially so by the onset of COVID, which catalysed the industry to redesign customer engagement during risk assessment. Customers value convenience and speed, placing traditional life insurance practices under scrutiny compared to other sectors, e.g., banking, that already provide digital customer engagement. Attracting, engaging, and retaining customers through the existing, and sometimes archaic on-boarding process is becoming ever more challenging, putting insurer margins at risk.

Insight from our global customer base tells us that insurers alike face a broadly consistent set of challenges from a new generation of customers that are well-versed in researching, buying, and reviewing products online but are not necessarily buying. The inconvenience, time and even nature of questions being asked are often intrusive and represent significant barriers to entry. Even those who have no intention of dropping out of the process may do so due to too many questions, doctors’ appointments, medical tests, blood tests, and requests for further details that frustrate the process.

As risk-bearers, the insurer and reinsurer have a somewhat different perspective. Life insurance, unlike general or health insurance, is a long-term guaranteed contract that spans decades. Underwriting is crucial to ensure adequate risk selection and pricing to provide long-term sustainability, and maintain customers' peace of mind at claims stage.

While insurers sympathise with the desire of a "one-click" buying experience, they face common challenges in maintaining competitive prices while addressing non-disclosure of risk factors by applicants, information asymmetry and anti-selective behaviour that underwriting aims to mitigate.

Ultimately, it is important to bear in mind that when it comes to transforming the underwriting experience, there is often a trade-off between a frictionless and fast onboarding process, customer acquisition costs, and future claims experience. Getting the balance right and managing risk complexity is a topic of growing focus for appointed actuaries and chief risk officers (CROs) when signing off the risks of AI models for future claims, regulatory compliance, and reputation. Munich Re's URE as the global market leader (used by over 130 insurers), laid the first foundation of digitisation, enabling insurers to transform their customer experience.

Munich Re is enabling insurers to transition to the next generation by precisely managing this risk complexity. This risk complexity is expected to only grow considering the worldwide societal and economic transformation unfolding through large language models like Large Language Models (LLM), GPT-4+, etc. Acquiring the required depth of capabilities however comes at a significant total cost of investment for insurers and years to set up but insurers need speed-to-market and competition is rapidly developing - it's therefore table stakes for insurers to prepare. A partnership with Munich Re has already enabled insurers to benefit from existing capabilities to accelerate the transition to the next generation of underwriting while having peace of mind from responsible AI regulatory compliance and appropriately managed risk from AI.

Traditional underwriting pain points as opportunities

For next-generation underwriting solutions to generate concrete value, their designs must be anchored in a deep understanding of the underwriting process, pain points in the customer and agent experience, UREs, how success will be measured and the resulting benefits . The following steps are typically involved in the traditional underwriting process:

Applicants complete an application form and disclose their medical and financial conditions. The former is needed for medical underwriting that assesses mortality/morbidity risk and the latter for financial underwriting that assesses the financial background to prevent over-insurance and anti-selection.

Depending on the medical disclosures in the application and the applicant's age and sum assured applied for, additional medical tests and reports **(see Table 1)** might be requested. The simplest form is a medical examination report by a physician comprising vital signs and general health conditions. At higher sum assured and ages, further medical evidence is required - from urine tests, chest x-rays, to blood profile tests, stress ECGs and Attending Physician's Statement (APS). An APS is a report by a physician, hospital or medical facility who has treated or is currently treating the applicant. The APS, in addition to the other medical evidence, provides a detailed medical history in addition to the self-disclosure made in the application form, thereby enabling identification of potential non-disclosure or misrepresentation.

Table 1: Sample medical requirements schedule (non-medical limits)

	Age			
Sum assured ($)	16-45	46-50	51-60	61-70
<200,000	No additional medical evidence needed			MER
200,001 - 250,000			MER	MER, ECG, MU
250,001 - 300,000			MER, CXR, ECG, MU	
300,001 - 500,000		MER, ECG		
500,001 - 750,000	MER, HIV	MER, ECG, HIV, MU, APS	MER, MU, BT, HIV, CXR, ECG-TM, APS	
750,001 - 1,500,000	MER, HIV, BT	MER, ECG, BT, HIV, MU, CXR, APS		

Legend

MER	Medical examination report
CXR	Chest X-ray
ECG	Electrocardiogram - resting
ECG-TM	Electrocardiogram - treadmill
MU	Micro urinalysis
APS	Attending physician's statement
HIV	HIV test
BT	Full blood profile

The medical underwriting process is cumbersome and inconvenient for applicants. Firstly, where paper application forms are used, these are often submitted incomplete or illegible and require a revised re-submission or additional queries from the insurer. Secondly, the inconvenience of a medical examination and related tests that sometimes trigger requests for further investigations/tests. Thirdly, it may take several weeks for an APS to be completed and a decision made on the application. Applicants therefore often drop off and don't proceed with the application. For the insurer, this means a missed new sale, irrecoverable incurred acquisition costs and a frustrated customer that may not re-engage.

Insurers' traditional solutions to manage inefficiencies in the new business process include:

Reducing the number of application form questions, that is, instead of a "long" application form with dozens of medical and financial questions ("full underwriting"), insurers reduced these to three to five questions ("simplified issue") or even no questions ("guaranteed issue"). The latter two are commonly seen in bancassurance.

Relaxing underwriting requirements, for example by increasing the non-medical limits. This does not address the actual process inefficiency but rather reduces the number of applicants that undergo full underwriting that therefore treats the symptoms, not the cause. From a risk management perspective, this generally results in a worse claims experience. A higher risk of anti-selection is also commonly observed, that is, applicants not providing full disclosure of their medical or financial situation that results in early claims or under-pricing. Unless these risks are adequately priced in and actively managed by the insurer, the technical result of the insurer will deteriorate over time. However, given the sales and price pressures faced by insurers, insurers often struggle to implement premium increases or tightening of underwriting requirements.

Munich Re's next generation AI-augmented underwriting now provides a solution to improve the customer experience, lower customer acquisition costs and enable sales whilst minimising risks for the insurer's future claims. Before discussing the next generation, it's helpful to recap the journey to date.

Evolution of underwriting to date

A significant improvement in customer experience came with the introduction of automated underwriting systems which digitised manual, paper-based processes.

Digitising underwriting information has become a strategic necessity in an AI- and data-driven world and further exacerbated by the COVID pandemic. Insurers that have implemented underwriting engines do have a significant strategic advantage over their peers. The availability of comprehensive underwriting data in a structured digital format significantly increased the opportunity to develop AI models and to implement them into production. The evolution of underwriting automation can be broken down into three generations, the first two mostly describing the evolution to date.

First-generation – jet engines: insurers digitised their systems in the transition from paper to electronic applications and implemented jet casing or clear-casing systems. Typically, these "engines" would allow application forms that had no disclosures to be expedited and checked with basic business validation rules. They sped up the onboarding process and provided a degree of efficiency but lacked transparency on their workings to enable insights for improving the underlying underwriting philosophy. Further, being mainly hard-coded rules, they offered limited ability for adjustment.

Second-generation – automated underwriting rule engines (URE): these systems introduced the concept "reflexive questioning" that aims to mimic how an underwriter would investigate medical disclosures. For example, if the applicant discloses high blood pressure, additional reflexive questions would be asked to assess the medical severity and reach an underwriting decision at the point of sale. This iteration gave insurers the opportunity to develop, review and amend their own underwriting philosophy. Reinsurers provided comprehensive expert underwriting rulesets based on their underwriting manuals. UREs could therefore increase underwriting automation and significantly increase the straight-through-processing (STP) rate depending on the underlying products, mix of business and underwriting philosophy. Changes in underwriting rules could also be carried out directly by the underwriters without the involvement of IT. This stage of system evolution added descriptive analytics capabilities via business intelligence dashboards and reports. These improvements allowed underwriters to closely monitor and analyse the performance of the underwriting ruleset and adjust to further increase the overall STP rate. However second-generation descriptive analytics had several limitations given the large number of risk factors that impact an underwriting decision, AI is clearly better placed to increase automation given its ability to learn complex (multivariate) relationships between risk factors and underwriting decisions. Further, only URE data is typically analysed which ignores back-office underwriting outcomes and similarly claims data is almost always ignored. In summary, second-generation descriptive analytics offers a very incomplete picture of the underwriting process and subsequent claims, and limited potential for improving the underwriting process.

The next (third) generation: AI-augmented underwriting

While second-generation solutions improved automation and the customer experience to a degree, many pain points remain (see Figure 1) that impact sales and profitability for insurers that the next generation can address.

For example, many insurers' UREs present room for improvement in STP rates since they may still refer a material number of applications for manual underwriting, often resulting in further medical or non-medical evidence requirements. Experience in delivering AI initiatives to several insurers shows that many of these applicants are observed to finally be decisioned as standard risks in the back-office final underwriting result, that is, the additional evidence requested - with hindsight - created unnecessary inconvenience for the applicant and customer acquisition costs for the insurer. Further, such applicants may withdraw ("not-taken-up") due to the inconvenience and the insurer may miss sales opportunities. To address this pain point, AI models are developed and deployed within the URE to predict the underwriting outcome (see Figure 1) and applicants with the highest probabilities of being a standard decision are approved in real time without further underwriting, thereby avoiding unnecessary referrals and increasing STP, resulting in a smoother customer experience.

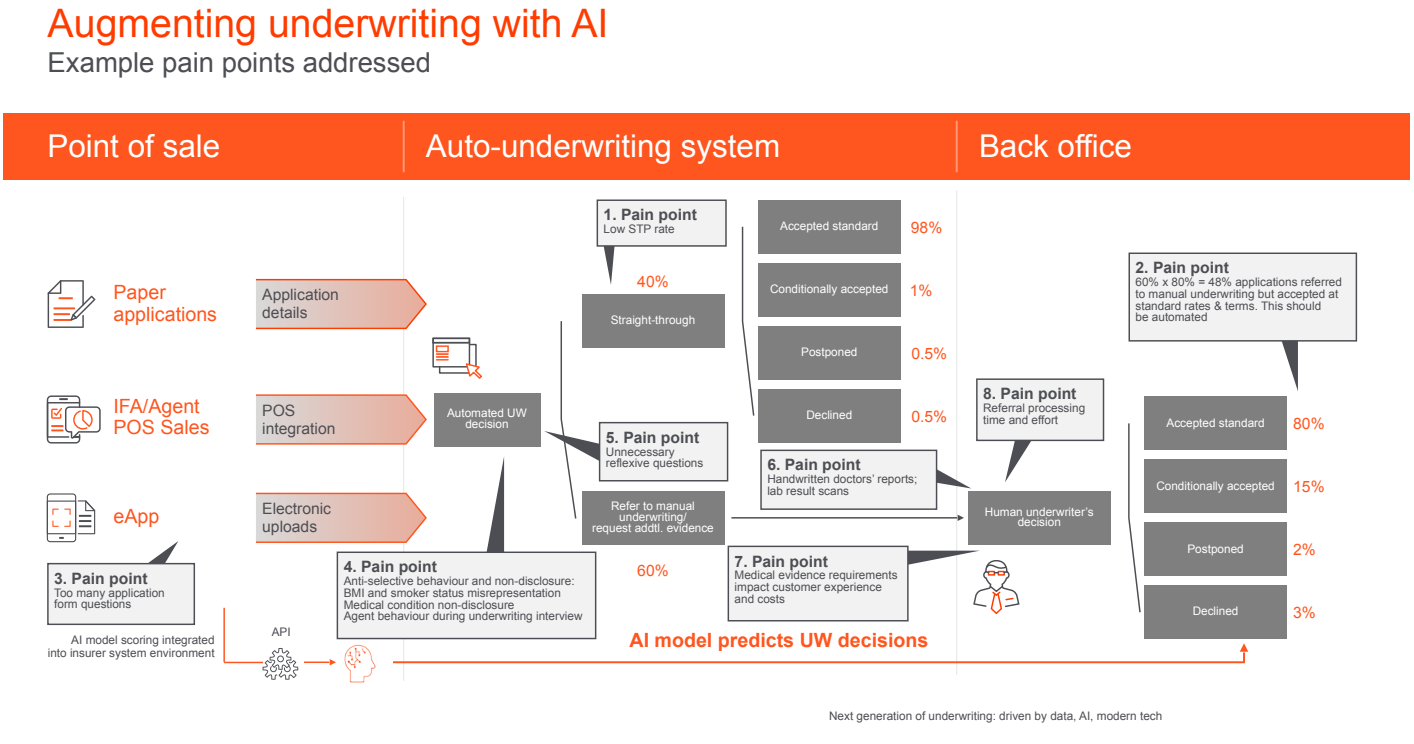


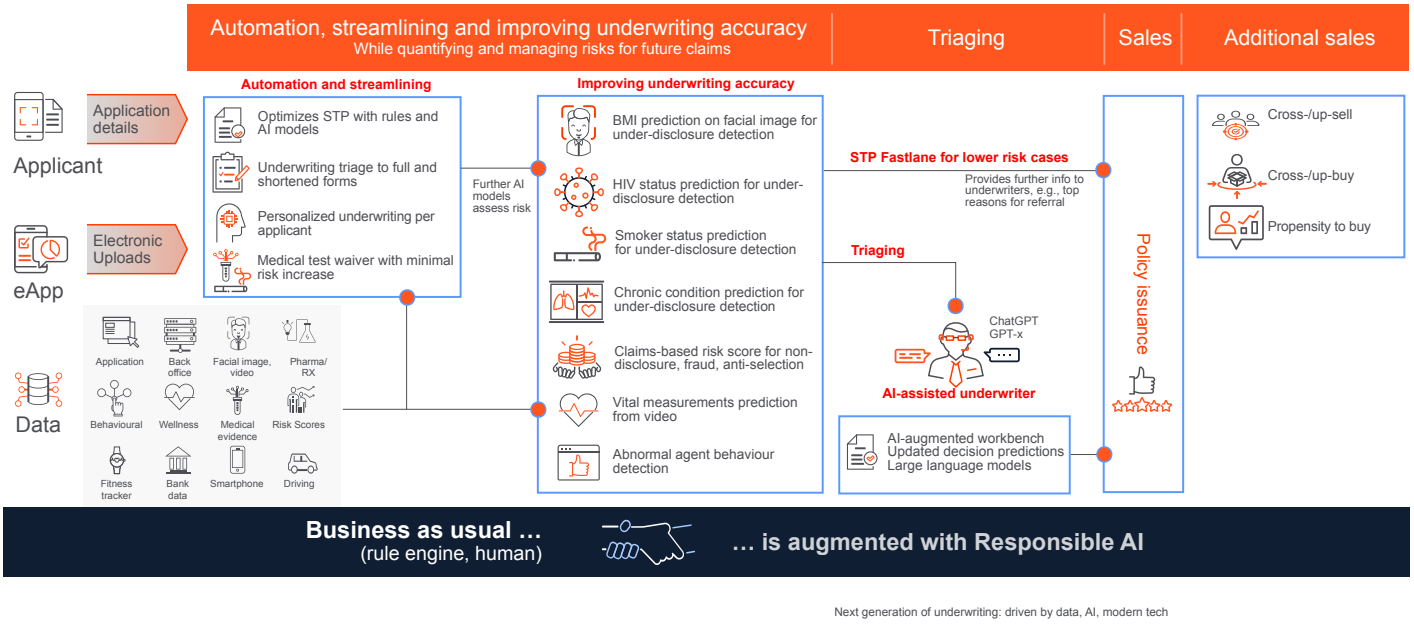
Figure 1: Examples of underwriting pain points addressed in the next generation with AI

Munich Re's next-generation AI-augmented underwriting solution offers point-of-sale risk assessment that improves automation (instant decisioning, higher STP), streamlining (of application forms, medical requirements, etc.) and customer triaging to improve the customer experience and reduce underwriting costs while also quantifying and managing the risks posed to insurers' future claims from AI model errors.

In addition, an innovative new feature is the ability to improve the accuracy of underwriting to increase profitability. This is achieved by integrating deep domain knowledge, internal and external data, UREs, AI models, actuarial risk sign-off on AI models, responsible AI regulatory compliance, and modern MLOps technology for implementing and maintaining AI models within insurers' business processes and systems. The automation, streamlining and improvement in accuracy is achieved through combining several AI models live into a single underwriting customer journey (**Figure 2 top**). The result is a true hybrid of the URE, AI and human judgement with the URE and AI decisions combined to reach final decisions in an automated way – truly the industry's first AI-augmented solution that brings insurers the best of UREs, data, AI, and other technologies. Next generation solutions will increasingly reduce friction to the customer by obtaining data sources earlier in the underwriting journey and without required action from the customer (**Figure 2 bottom**). These either infer answers to existing underwriting application questions or offer new insights into the risk through external data and new model scores.

Next-generation AI-Augmented underwriting solution

Augmenting underwriting with Responsible AI, Data, Modern Technology



Next generation of underwriting: driven by data, AI, modern tech

Future customer journey has reduced information asymmetry through earlier and wider data collection on customer risk profile - fewer UW questions required and better risk classification

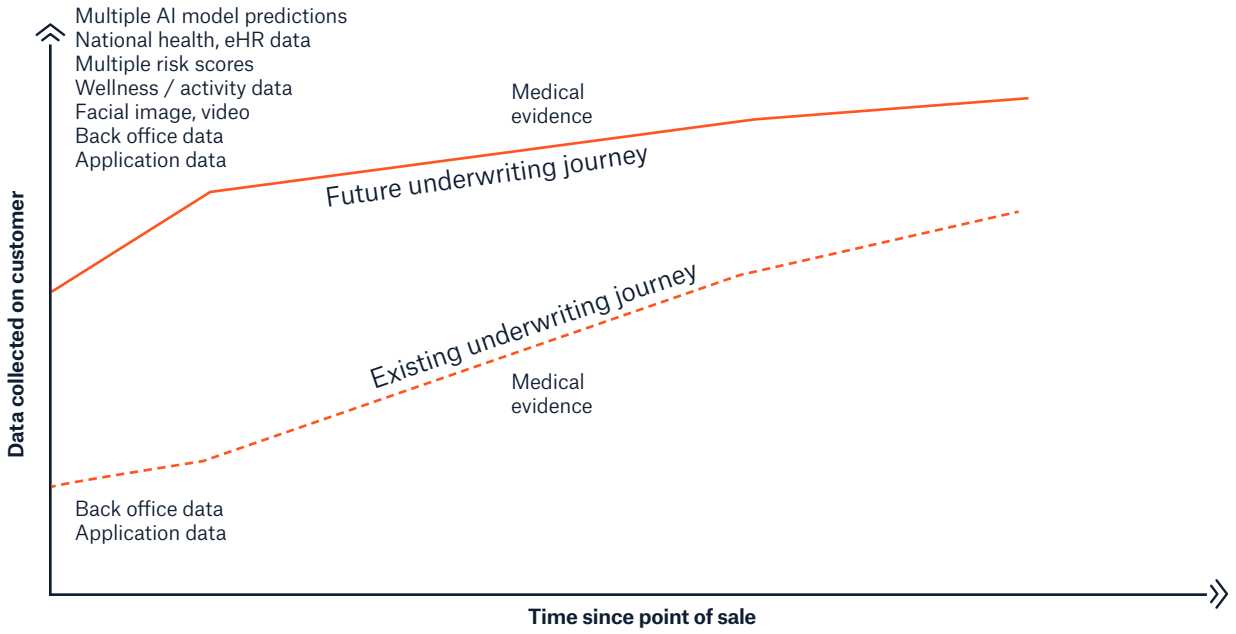


Figure 2: Munich Re's AI-augmented underwriting solution uses multiple data sources, AI models, and technologies to transform the underwriting journey

To further emphasise the additional benefits to insurers from the next generation:

Automation extends beyond increasing the STP rate to also consider the holistic customer experience. For example, a URE decision may be STP, but medical requirements may still be required which deter customers from completing the sale. The next generation can further reduce customer friction by selectively waiving medical questions and medical requirements (for example, smoker test, HIV test, etc.).

The second generation lacked a data-driven scientific approach to quantifying the risks posed to insurers' future claims by increasing STP or streamlining underwriting. As a result, improvements that were possible under the second generation were conservatively approached, often with high price loadings to fully underwritten rates or inadequate loadings that impact profitability. The next generation better optimises the trade-off between streamlining underwriting and pricing and therefore is more valuable to customers and insurers' sales. By using a more robust scientific method and comprehensive risk implication reports, actuarial risk management teams are better empowered to assess and approve underwriting enhancements.

By leveraging data sources like claims experience and external data, more accurate underwriting is possible. Automating underwriting decisions simply replicates human decisions (and the underlying underwriting philosophy) at scale – but this does not reduce the impact of inherent limitations of such decisions on downstream profitability (the disconnect between underwriting and claims). For example, the lack of a feedback loop to incorporate the subsequent claims experience into underwriting or addressing under-disclosure at the point of sale instead of at claims stage. The next generation can improve the accuracy of underwriting by applying AI models that use data from UREs and back-office systems (underwriting and claims) and additionally, where available, external data. These models offer point-of-sale predictions of under-disclosure (for example, smoker status, HIV status, BMI, other medical disclosures, etc.) and, for the first time in the industry, predictions of future claims using URE data. The latter was typically only possible using rating factors used in pricing bases – a major limitation of this was that highly predictive risk factors available from URE data were ignored. Exploratory data analyses of URE, back-office and claims data suggest anomalies between insurers' underwriting philosophies and their subsequent claims experience. Historically, this anomaly is only possible to correct years later in the pricing basis if sufficient claims data are available. Now, with AI models applied at the point of sale, the opportunity exists to intervene much earlier to better align underwriting and claims to improve profitability.

In summary, insurers can expect innovative new features in the next generation underwriting journey:

Multiple AI models are applied in real time at point of sale to address multiple pain points.

Orchestrates UREs and AI models in a new underwriting process to leverage strengths of both. Increased STP allows for automation from both the URE and AI model.

Flags applicants at the point of sale who are most likely to non-disclose, file early claims or anti-select – especially important in digital sales without face-to-face interaction.

Detects possible non-disclosure with deep learning models that predict underwriting risk factors (for example BMI) from unstructured data such as customer images and videos.

Use AI models to understand the value of external data such as physical activity, lifestyle, bank, or retail data to enable simplification of underwriting.

Incorporates historic claims experience in AI models for underwriting.

Telemetry (behavioural analytics) gathers data on and identifies anti-selective agent behaviour from the web-based digital underwriting application.

Enables effective cross- and up-sell/buy or next-best-offer initiatives with simplified underwriting.

Agnostic to different automated underwriting rule engines.

AI models deployed as REST API endpoints to allow streamlined integration and orchestration.

Future-proofs insurers by leapfrogging barriers to deploying AI cost-effectively and at speed. Uses modern IT technology for supporting MLOps to achieve scale and cost- effectiveness when deploying and maintaining AI models.

Follows modern MLOps practices to monitor model performance and efficiently and continuously maintain (retrain) AI models to ensure they perform as expected and manage risk implications for future claims experience.

Responsible AI frameworks to comply with insurance regulation that covers fairness, ethics, accountability, and transparency.

In summary, benefits of augmented underwriting with AI include:

Increases STP, thereby enhancing the customer experience by shortening onboarding times.

Streamlining the application form to reduce friction to customers.

Reducing medical requirements to improve the customer experience by waiving unnecessary medical tests (HIV, smoker, BMI medical verification, etc.)

Increases the accuracy of risk selection.

Increases underwriting capacity without increasing staff count.

Reduces referral processing effort and customer acquisition costs.

Improves profitability by reducing the impact of anti-selection.

Audits at scale without expanding the underwriting team.

Why deep domain knowledge is needed to manage the risk complexity of AI-Augmented Underwriting

Below we deep dive into a few dimensions of the risk complexity from AI-augmented underwriting to illustrate why deep domain knowledge and expertise is needed to manage these challenges confidently.

As mentioned, it's really the interplay between so many capabilities (**see Figure 3**) across the AI lifecycle that determine success in the end. In particular understanding the interplay of the insurer's various IT systems in generating data that reflect that underwriting journey and its outcomes which impact the customer onboarding experience, for example, point-of-sale (front end), URE and back-office systems. Balancing a smoother customer experience involves a level of complexity that insurers have simply not had to manage before including operational, AI-specific cloud technology stacks, AI regulation and the risk implications of AI model error for insurers' future claims requires. Only through a deep understanding of all these topics and how they interact, is success likely.

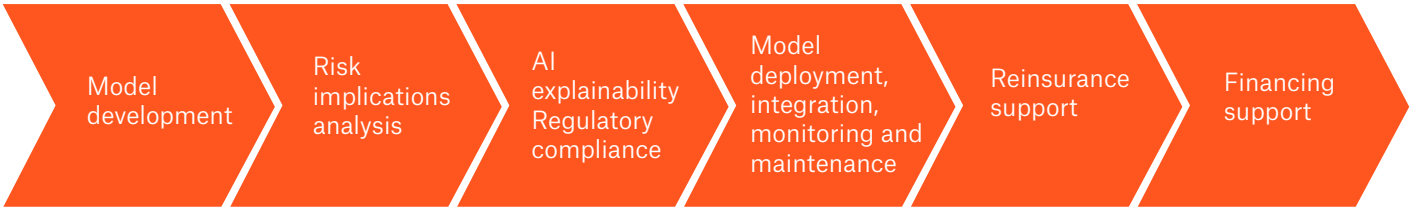


Figure 3: Capabilities needed to successfully deploy AI

For example, prior to deploying AI models to increase STP, insurers and actuaries need to obtain sign off on the risk implications of AI model errors (for example, false positives) for future claims experience from their risk management teams/appointed actuary/CRO, etc. To address this, Munich Re developed comprehensive AI risk reports and has also had the experience in achieving sign off to know the frequently asked questions and how to satisfactorily address them. For example, when increasing STP, **Figure 4** illustrates that when an AI model incorrectly predicts that an applicant should be underwritten as a standard risk, a false positive error occurs and the applicant should be conditionally accepted, postponed or declined. The higher the frequency and severity of such false positives, the greater the expected impact on future claims and hence the higher the adjustment required to best-estimate pricing to absorb the impact. Deep underwriting and actuarial knowledge are required to correctly interpret and translate the risk profile of false positive cases into extra-mortality/morbidity assumptions at the granular level, including the analysis of complex medical conditions and exclusions. Senior actuaries will have a keen interest in the robustness of the model performance to a changing mix of business and this will require properly designed scenarios to ensure pricing adjustment resilience.

Figure 5 provides an example of Munich Re's AI risk implication calculator that assesses, for each level of STP, both model performance (data science) metrics and best-estimate pricing (actuarial) adjustments. Further, deep underwriting and actuarial knowledge is needed to design effective risk guardrails to govern how the model is used. For example, knock-out criteria determine which cases should be allowed to be decisioned by the model and random holdout samples ensure the model performance can be compared against the traditional underwriting decision to ensure model performance is as expected in product. Other validation includes checks and balance to ensure the data reaching the model for predictions passes quality standards. Setting effective criteria require deep actuarial, underwriting, operations, and data science expertise. Munich Re's calculator enables these risk guardrails to be adjusted and all other metrics automatically be recalculated, thus allowing the solution to be optimised to an insurers' risk appetite.

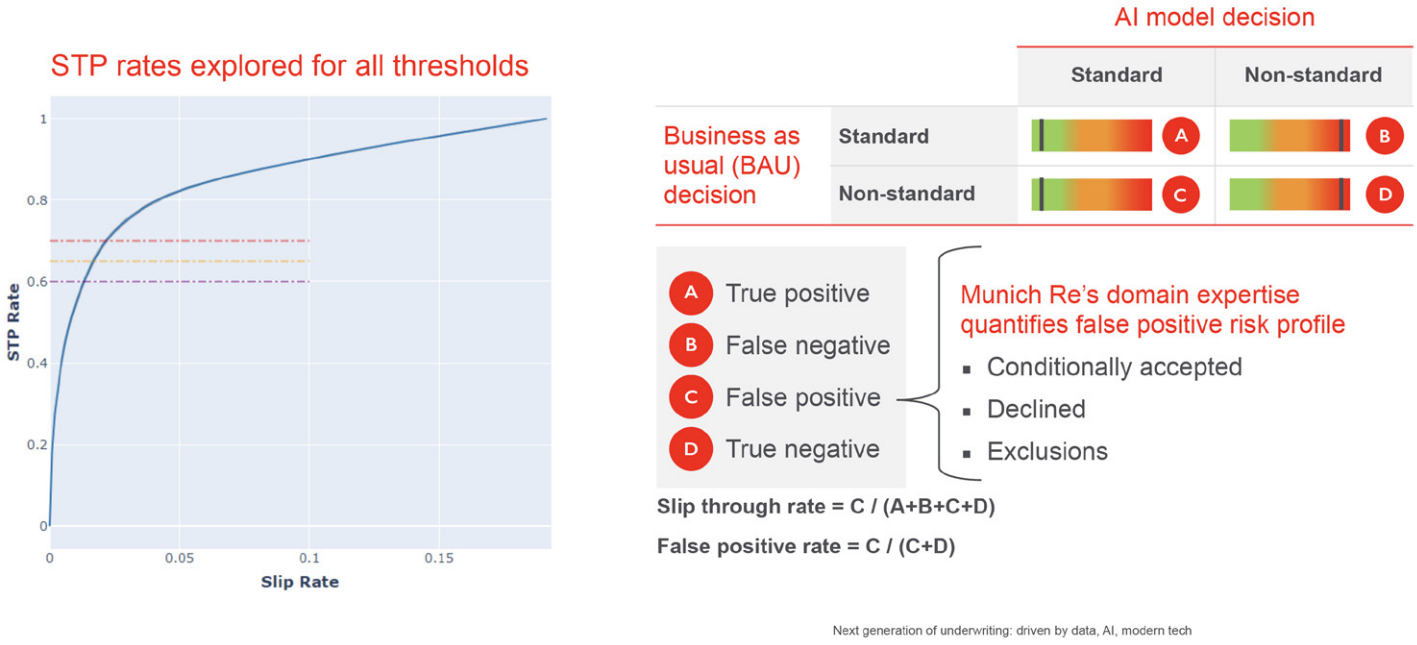


Figure 4: Example of AI model risk implications associated with different STP rates

Compliance with responsible AI (RAI) regulations, now published by many regulators, is essential before deploying AI live into insurer business processes and systems, especially when the nature of the use case can potentially disadvantage customers. Munich Re is a member of the VERITAS industry consortium set up by the Singapore regulator (MAS) to develop RAI principles and tools. Importantly, insurers need to know how to implement the principles of RAI into metrics that are appropriate for their use cases. For example, using our domain knowledge, Munich Re developed RAI model bias metrics that are tailored for underwriting use cases and comprehensive tools and processes to ensure RAI compliance (**Figure 6**).

For example, prior to deploying AI models to increase STP, insurers and actuaries need to quantify and manage the risk implications of AI model errors (e.g., false positives) for future claims experience. When increasing STP, **Figure 4** illustrates that when an AI model incorrectly predicts that an applicant should be underwritten as a standard risk, a false positive error occurs and the applicant should be conditionally accepted, postponed, or declined. The higher the extent of such false positives, the greater the expected impact on future claims (profitability) and hence the higher the adjustment required to best estimate pricing to absorb the impact. **Figure 5** provides an example of an AI risk implication calculator that assesses, for each level of STP, both model performance metrics and best-estimate pricing adjustments. Further, the impact of risk management controls like knock-out criteria and random holdouts is incorporated. Such capabilities require deep actuarial, underwriting, operations, and data science expertise. These tools also ensure models are compliant with fairness, equity, accountability and transparency (FEAT) regulations.

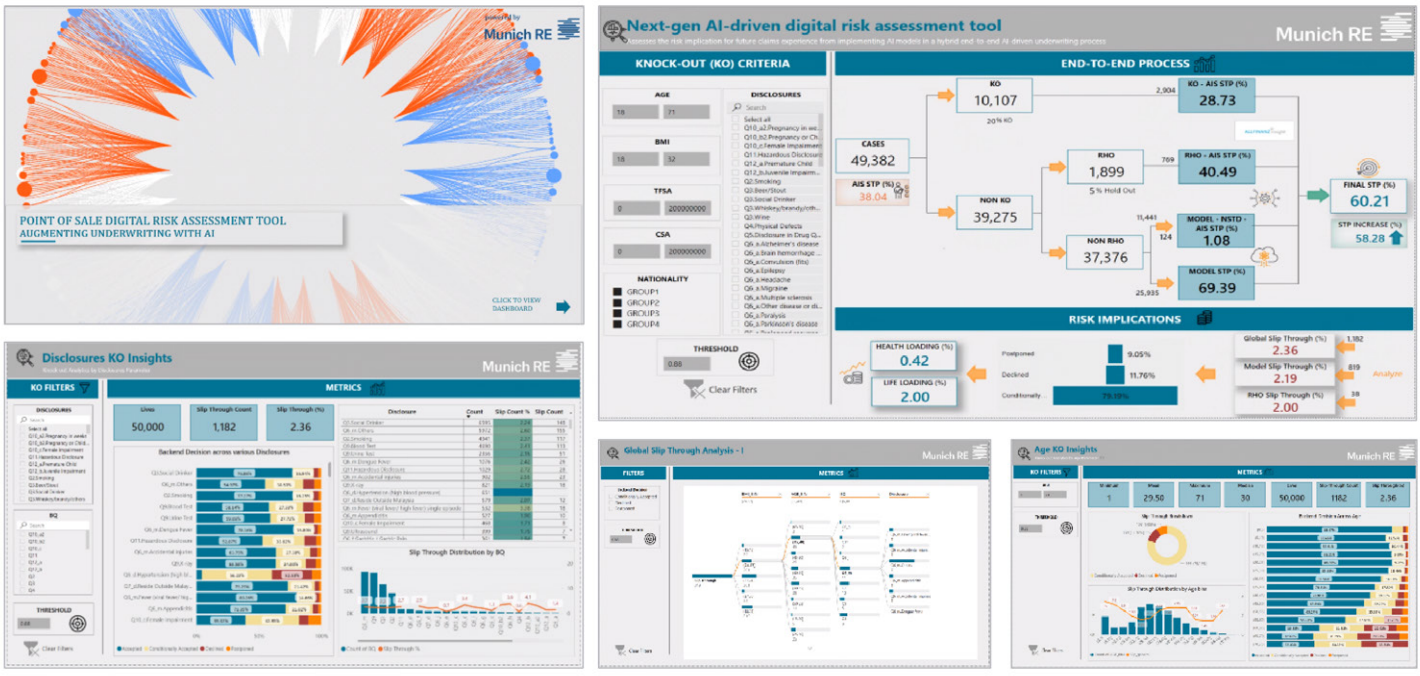


Figure 5: AI risk implication calculator

The new underwriting process (example in **Figure 7**) must be defined and address exactly how the model prediction will be consumed by the URE, which cases follow the URE decision, and which follow the AI model, how the knock-out criteria and random holdouts are applied in an automated way, etc. This requires knowledge of URE rulebooks and rule development, and testing of the new rulebooks. The next generation underwriting process will increasingly require insurers to integrate and orchestrate multiple AI models in a single underwriting process and hence such integration capabilities are key for implementation.

Responsible AI compliance

Our already-developed capabilities ensure compliance with AI regulations

Bias detection and mitigation

Define, detect and mitigate bias through a range of metrics and algorithms

Explainability and transparency

Distil AI decisions for higher transparency and debugging

Monitoring and governance

Monitor AI solutions for data drift, profile change, model errors and governance of the whole solution

Privacy, ethics and regulations

Ethical and regulated implementations of AI based on guidelines from insurer and regulator

Risk implications

Detailed cost implication of implementing AI solution encompassing the cost of errors from model, reputational risks, cost of human capital

A successful AI model achieving stakeholder adoption and regulatory compliance includes sign off on all relevant risk and AI regulations. Munich Re is an official member of the MAS Veritas Consortium that developed Responsible AI principles and practices for insurers in Singapore.

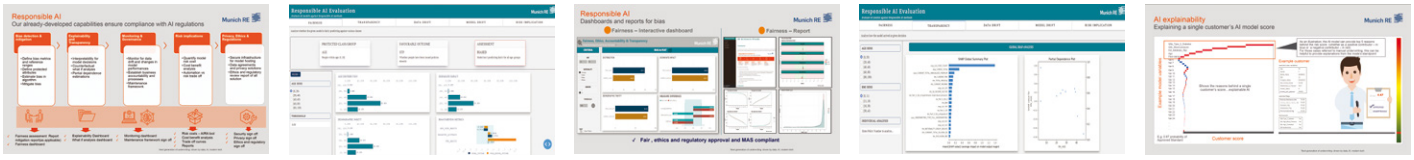


Figure 6: Underwriting process flow integrating model predictions into URE

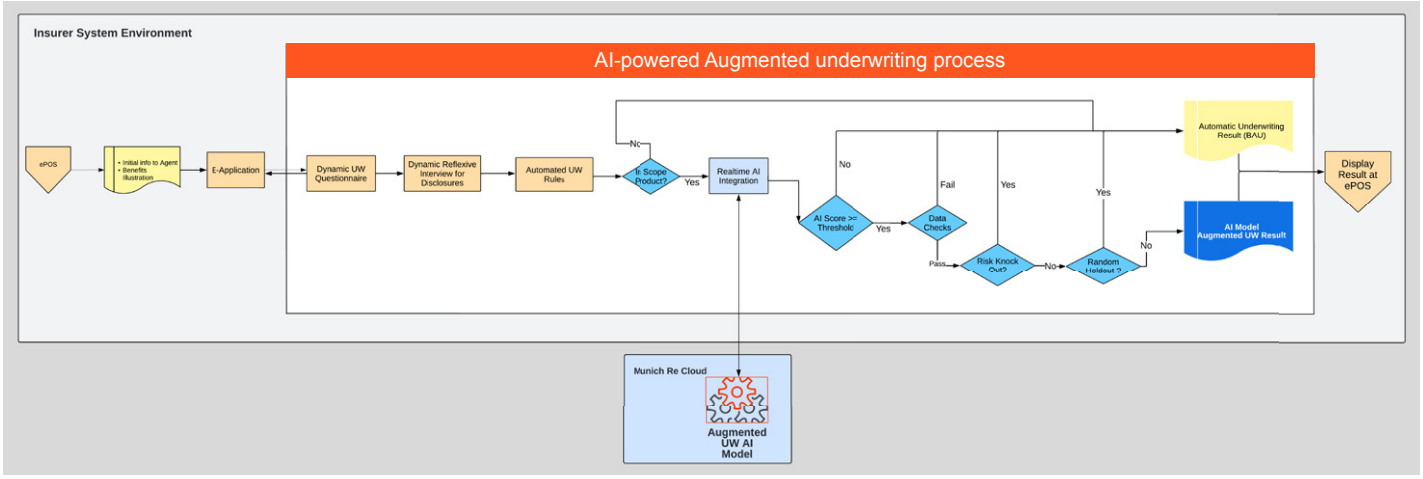


Figure 7: Underwriting process flow integrating model predictions into URE

Before the new underwriting process can go live, the model API must be possible to integrate into the insurers' URE and systems environment. As developer of the URE most widely used by insurers, Munich Re's rule engine is the only one capable of integrating a model API within the URE to enable real-time scoring at point of sale.

This requires proprietary capabilities such as an API mapping tool and rule developer (**Figure 8**) without which a model simply cannot be implemented into the URE for true point-of-sale underwriting automation with AI. Some insurers have integrated models with back-office systems (which doesn't achieve real uplift in STP at point of sale) and some insurers follow a human-in-the-loop approach (effectively the model becomes a recommendation engine and doesn't achieve the real underwriting automation from overriding a URE decision with an AI model decision at point of sale).

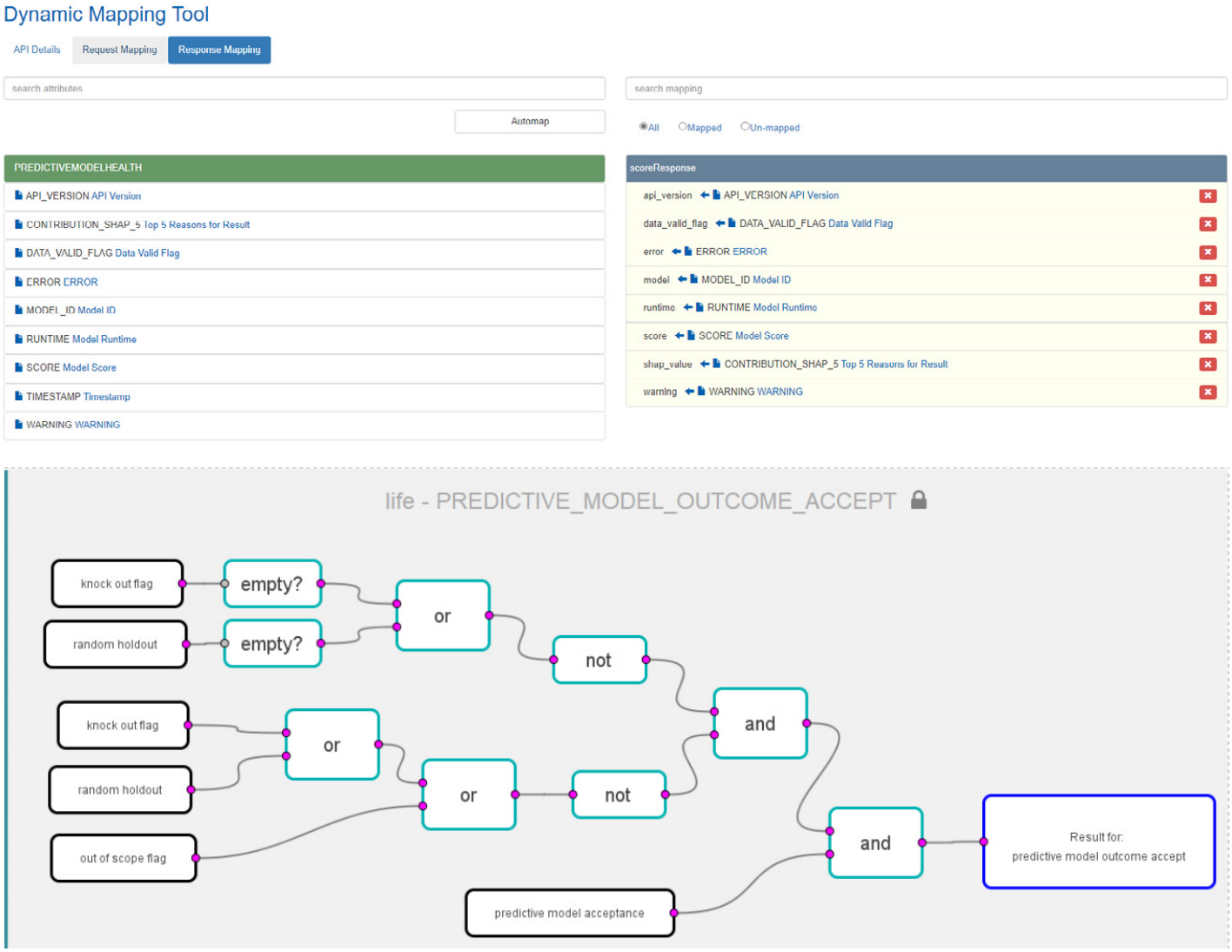


Figure 8: Integrating AI model predictions into URE via Munich Re's API mapping technology

Before going live, processes and tools are needed to monitor the model performance in production not only for RAI compliance but to protect an insurer's bottom line from increased claims risk in the future and achieve sign off from risk management. Again, using our deep domain knowledge of underwriting, we have developed comprehensive monitoring dashboards to monitor the relevant business KPI trends (for example, STP), several model performance metrics and the mix of business (**Figure 9**). This is critical to timely model retraining (updating a model with new data) to ensure stable model performance (**Figure 9**), that is, avoid model drift.

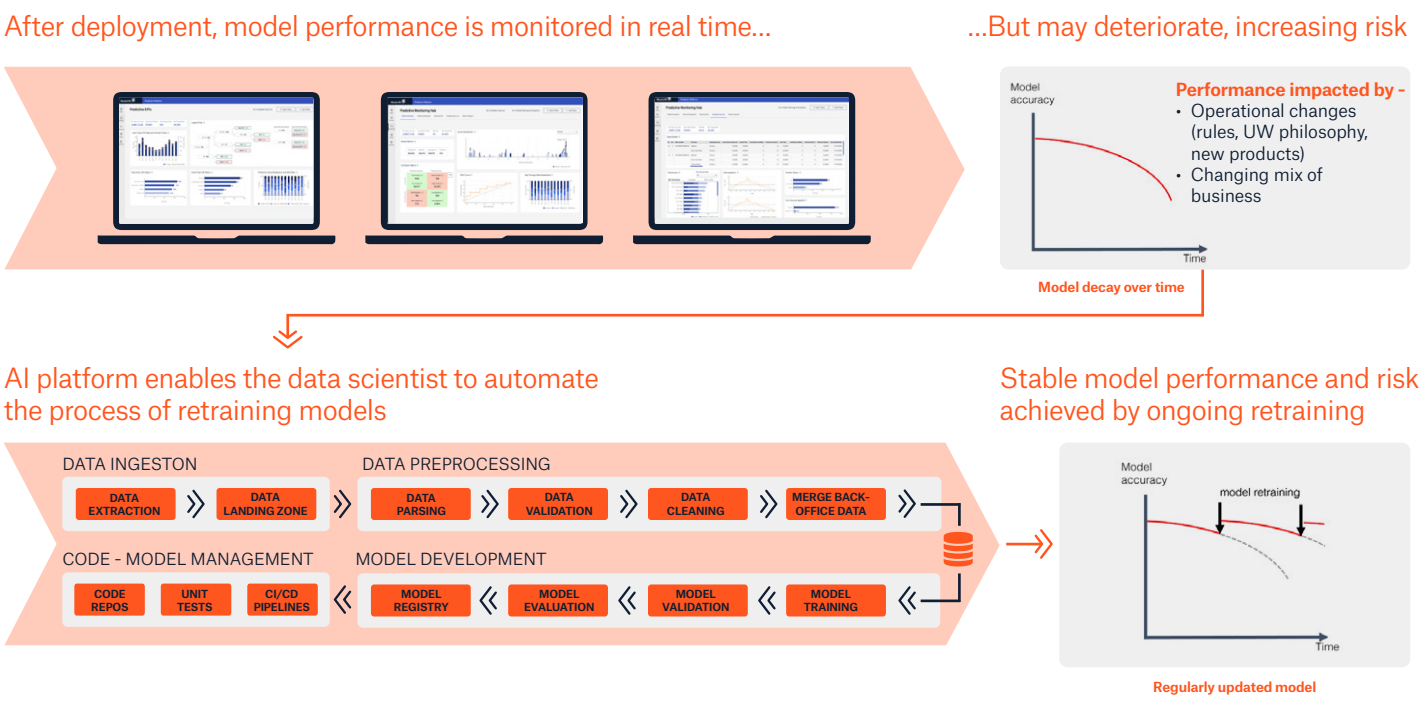


Figure 9: Underwriting process flow integrating model predictions into URE

Data scientists must be able to retrain models when required without causing significant disruption to the insurers' IT teams and production systems. Model retraining must be done reliably and rapidly. This is precisely what MLOps practices and technologies enable (**Figure 10**).

What is MLOps as the core of the AI platform?

Machine learning DevOps (MLOps) is a specialized subset of DevOps tailored to produce ML applications.

MLOps is both a technological and cultural shift that requires the right people, processes, and tools to successfully implement.

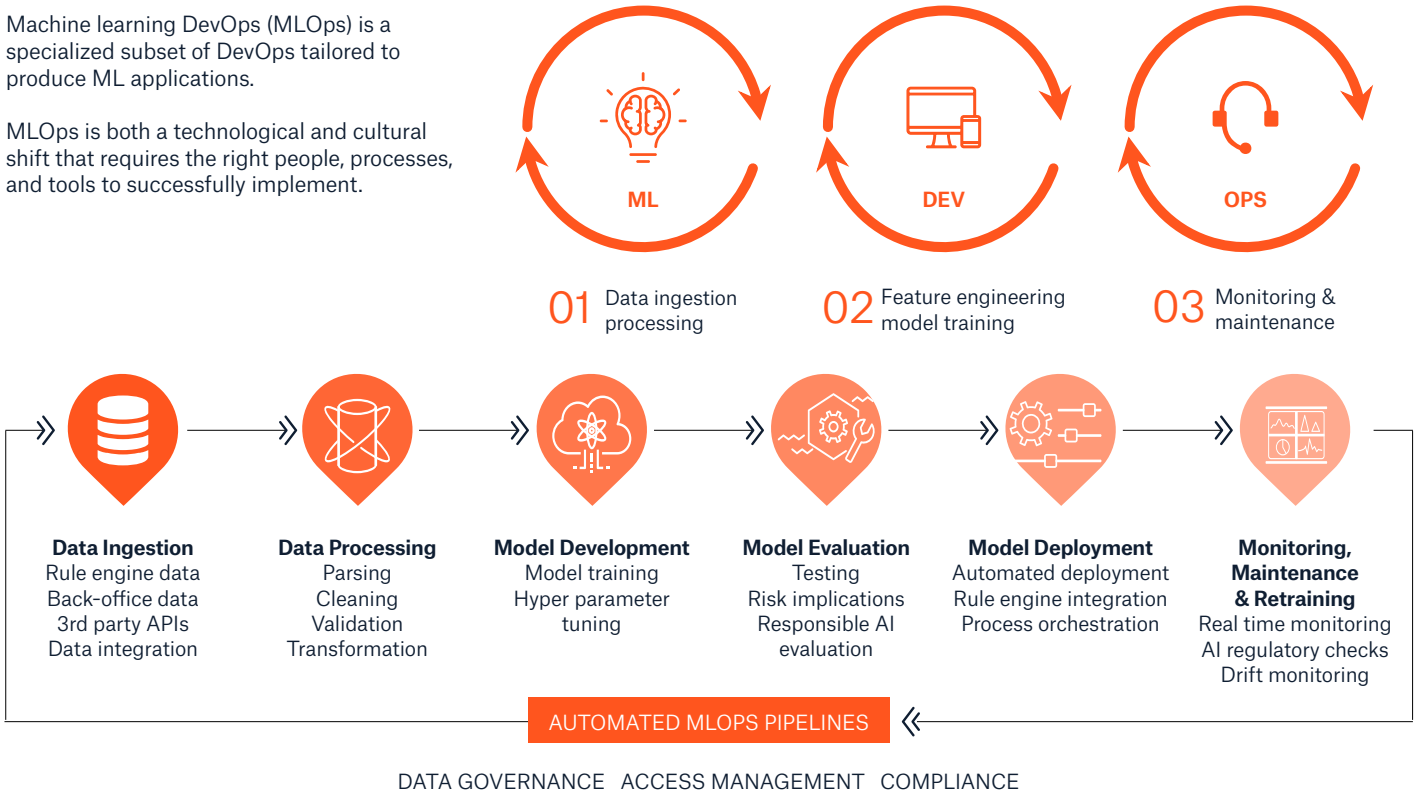


Figure 10: Basics of MLOps

Munich Re's AI platform (Predictor) ensures that our AI-augmented underwriting solution models are maintained for our clients with modern MLOPs technology practices. This in turn ensures models can be retrained rapidly, resulting in stable model performance and pricing reflecting the future claims experience for the business using the models. A commonly overlooked topic is who insurers call when issues arise in production. Munich Re offers round-the-clock operations support on its AI-Augmented underwriting solution to ensure that any incidents in production are dealt with within acceptable service-level agreements (SLAs) and insurers can have peace of mind from stable underwriting operations.

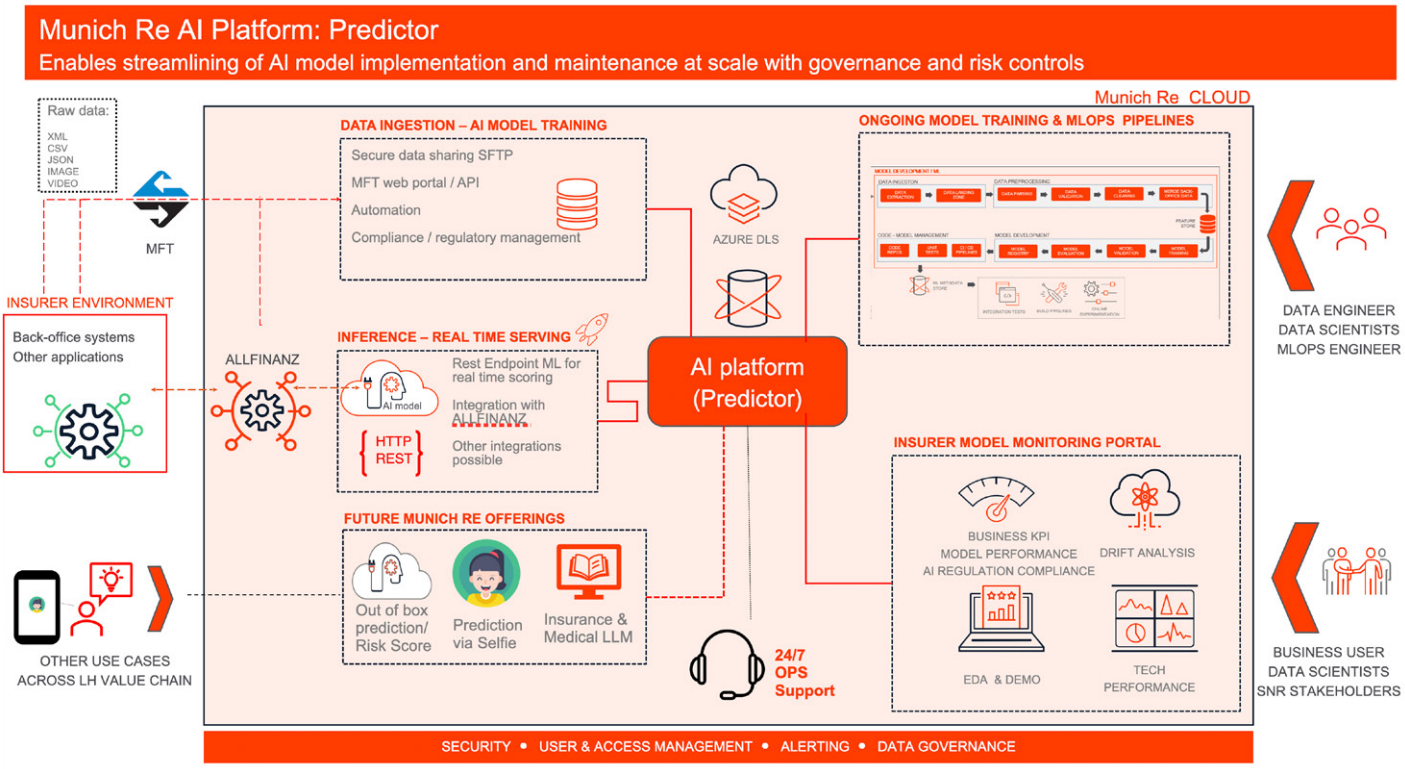


Figure 11: Munich Re's Predictor platform, an end-to-end AI (MLOps) platform for model production incorporating Munich Re Automation Solutions' ALLFINANZ SPARK solution.

Conclusion

Digital transformation has resulted in a continuous improvement of a traditionally paper-based and tedious underwriting process. Underwriting automation through rules-based expert systems is, and has been, the starting point for life insurers to improve the customer experience and operational efficiency. The digital underwriting data collected puts insurers at a significant strategic advantage over their peers in the current transition towards utilising AI to transform their underwriting and claims processes.

New data sources are expected to be introduced as proxies for traditional underwriting requirements, to avoid medical tests and move toward fluidless underwriting, where justified, from an AI and risk management perspective. Reinsurers play a leading role in vetting these solutions, that is, quantifying the risk impact on the mortality and morbidity experience.

The stage and maturity of the underwriting transformation varies widely by region and insurer. North America has industrialised use of third-party data in AI models already, whereas in Asia-Pacific (APAC), many large insurers have deployed third-generation underwriting engines and early adopters in southeast Asia are moving to the fourth-generation, that is, augmented underwriting with AI.

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About Munich Re

Munich Re is one of the world's leading providers of reinsurance, primary insurance and insurance-related risk solutions.

Munich Re Automation Solutions, a Munich Re subsidiary, is the world leading provider of digital new business, underwriting and analytics solutions to the insurance industry. Working with forward-thinking customers across the globe, we're on a mission to revolutionise the way life insurance is bought and sold, using next-generation technology to give insurers the power to grow their businesses profitably.

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