Artificial intelligence in health insurance

Smart claims management with self-learning software

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Artificial intelligence (AI) is one of the current megatrends emerging from the broader digitization of society and the economy. So far, these "smart" AI technologies have mainly attracted attention in the e-business, automotive, and consumer goods sectors. Siri, the automated voice on Apple's iPhone, or Alexa, Amazon's electronic shopping assistant, are two examples shaping public perception. Automated image recognition systems and self-driving cars are making a mark as well.

The private sector has long recognized the potential inherent in the new technologies. Self-learning software and cognitive systems can either already be found throughout the value chain or are on the verge of deployment: forecasting and pricing tools for purchasing and inventory management, chatbots for customer service, delivery drones for the last mile. AI applications can help companies to optimize services and lower costs, accelerate processes, and make better decisions.

A similar development is taking place in the healthcare sector, although exploration of the possibilities that artificial intelligence offers in the field of medical care and management is in its early stages. The most progress to date has been made with AI use cases around providers: medical centers are increasingly using early detection systems supported by algorithms or automated recognition of patterns in patient data.

Less known are the opportunities that the use of smart technology enables for health insurers. Initial use cases have been found for AI-supported systems that enhance care – for instance, in the development of customized offers for patients suffering from chronic diseases or for identifying clinical pathways that fail to adhere to guidelines.

Yet artificial intelligence is capable of more. Cognitive systems can help case managers to efficiently screen cases, evaluate them with greater precision, and make informed decisions. Hospital claims management is another area that stands to benefit. A look at the situation in Germany illustrates the extent of the possible gains. The nationwide cost of inpatient treatment amounts to EUR 73 billion and makes up 30 to 40 percent of a typical health insurer's total budget; on average, however, between 8 and 10 percent of all claims received are incorrect. Reliably identifying and correcting these incorrect claims would save all stakeholders – health insurers and providers alike – a great deal of time, money, and effort.

Artificial intelligence can achieve this objective. The conventional approach to claims management based on an inflexible rule book has been made obsolete by intelligent algorithms that learn from historical cases and continuously evolve. Such a system can systematically identify and correct errors while avoiding unnecessary or ineffective interventions. First estimates indicate that German health insurers could save in about EUR 500 million each year this way.

In the following we examine how this opportunity can be seized and the preconditions for successfully establishing AI-supported claims management. After a brief discussion of the technological fundamentals of artificial intelligence, we describe in detail the cognitive systems that can be used in hospital claims management, their impact, and the steps needed to ensure their effective operationalization.

Trending term "artificial intelligence" – and what lies behind it

Like other examples of jargon from the digital world, artificial intelligence is a common and frequently discussed term – but few have a precise notion of what it actually means.

In fact, artificial intelligence encompasses a broad range of methods and technologies that make software smart enough to draw on data in order to autonomously control machines, produce forecasts, or derive actions. To this end, the smart systems use advanced algorithms that learn with every additional data record and continually adjust and enhance their predictions.

In contrast to machine-learning technologies – which can likewise track developments, recognize patterns, and classify them – artificial intelligence is able to apply what it learns to new situations. AI systems don't just learn from experience, they distance themselves from the context that originated them and independently glean additional knowledge, thereby steadily advancing into new cognitive terrain.

The boundaries between machine learning and artificial intelligence are not always clear in practice. Many of the systems in operation today are hybrid solutions comprising multiple technologies.

The use case around hospital claims management relies on a cognitive system: a software architecture that emulates cognition and is able to derive conclusions from complex issues and make informed decisions.

Cognitive systems in hospital claims management – current practice and potential

Status quo: manual claims management

With its mature healthcare sector and broad range of statutory and private insurers, Germany offers a good context for examining developments affecting health insurers. A mid-sized German insurer with over 1.5 million members receives more than 700,000 claims for cost refunds from hospitals every year. Insurer have a duty to verify whether the claims are correct – a task that regularly ties down several hundred employees. Our experience across different health insurers has shown: almost one in ten claims is incorrect and the claim's amount can be challenged by the health insurer[1].

This process is extremely cumbersome. As a rule, as many as 70 percent of claims are flagged as unusual – i.e., as potentially incorrect – based on the health insurer's specific rule book. Administrative staff then check these claims in detail. Based on the claim information and any available patient history data, the staff then draw on their experience to decide whether or not to intervene (Exhibit 1).

Exhibit 1

The current process for hospital claims management is cumbersome and inefficient

SOURCE: McKinsey

Objections succeed for only about 10 percent of all "unusual" claims. Hence, a mere 10 percent of the "unusual" cases are successfully intervened. That makes it even more important to reliably identify claims for which intervention is likely to pay off. This goal is especially critical because the number of incorrectly challenged hospital claims is growing – a result of a higher number of inpatient cases combined with ever-tighter personnel capacity at insurers. Claims audits absorb valuable manpower, time, and resources that could be put to better use elsewhere – not just at health insurers, but also at providers.

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1 In Germany, statutory health insurers cannot reject a claim, but they can challenge the size of the claim.

Moreover, incorrect claims amounts that should not be paid but slip through the cracks in audit procedures constitute additional financial potential waiting to be unlocked. At present, health insurers could, in an ideal scenario, reduce the total amount of money originally submitted in claims by about 3 percent – significant savings from which both the insurer and the insured community benefit. However, this level of success is premised on the accurate identification of all claims for which intervention is likely to be successful.

AI-based claims management: high hit rate coupled with low effort

Smart audit algorithms enable reliable identification of those, and only those, claims that are in fact incorrect. AI approaches aim to identify only those claims for which the likelihood of successful intervention is high and, conversely, to route unobjectionable cases and those unlikely to result in successful intervention toward fully automated background processing so that administrative staff can effectively focus their capacity on cases that require review.
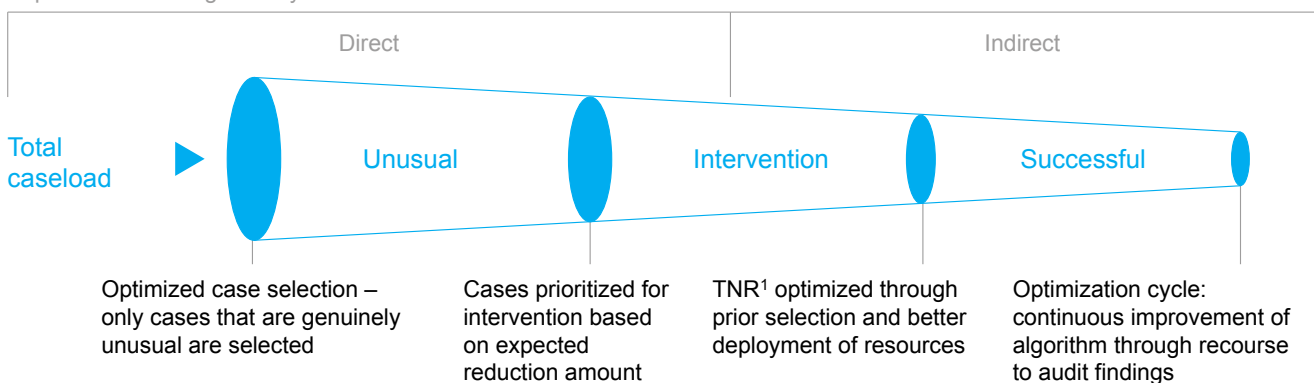
Exhibit 2 illustrates how the system works: in a first step, all claims received are checked to see whether they are correct, and any unusual claims are filtered out. Artificial intelligence is used to identify correlations among unusual claims which help determine the likelihood of a successful intervention; the system learns with every new claim received.

Exhibit 2

Cognitive systems help to reliably filter out incorrect claims and successfully reject them – thanks to smart and self-learning algorithms

Potential along the audit process

Impact funnel of cognitive system

Direct		Indirect	
Unusual	Intervention	Successful	

Total caseload

Optimized case selection – only cases that are genuinely unusual are selected

Cases prioritized for intervention based on expected reduction amount

TNR^1 optimized through prior selection and better deployment of resources

Optimization cycle: continuous improvement of algorithm through recourse to audit findings

Algorithm selects the most promising cases for intervention – auditing and intervention by auditors still necessary

1 Total net reduction

SOURCE: McKinsey

Claims deemed unusual are then automatically prioritized based on the reduction amount that can be expected and the likelihood of successful intervention. As a result, the system relieves the auditor from the need to make as many time-sensitive intervention decisions – freeing up capacity for those cases in which intervention is certain to yield results or for handling other tasks. Next, the system additionally provides the auditor with guidance on how to approach the intervention, for instance by suggesting grounds for rejecting the claim. The result is a simpler, faster claims management process – up to and including the intervention itself.

Developing cognitive systems in five steps

Smart systems for supporting hospital claims management are typically developed in five steps: compile and preprocess data; analyze data; develop the model; evaluate the results; and pilot the approach.

The first step, compiling and preprocessing suitable data, is anything but trivial given the vast amounts of data that health insurers have to process (with volumes at "big data" proportions). A key element here is the diligent cleansing and transformation of data that the cognitive system will later draw on; completeness and consistency are essential. The test data set should comprise historical patient data and data of claims where the amount of money paid was successfully lowered in the past.

Various statistical models are then used to analyze data on patients, diagnoses, and claims. At this stage, it is already possible to determine correlations between certain diagnoses and successful reductions.

This analysis provides a basis for developing a valid model for tagging claims anomalies. The test data is then used to train the cognitive system. By feeding in additional insurance data and external information – e.g., on the regional distribution of providers – the model is gradually enhanced until it eventually starts to independently learn new data and case patterns.

In order to conduct a subsequent assessment and select the system that will ultimately be used, several cognitive systems are programmed and then benchmarked in terms of specific metrics. Finally, the system is chosen that can most reliably predict the likelihood that a claim can be reduced successfully.

The final piloting phase serves to audit new claims received in real-world conditions and refine the algorithm further.

Prerequisites for establishing an AI-based system for claims management

Building an AI system is clearly a complex undertaking. The steps laid out above assume that the insurer has reached a stage in its development that will enable it to tackle such a major effort. Insurers considering the use of an AI system in claims management should therefore make sure that they have the all elements of a solid foundation for success:

Digitized original claims. Incoming invoices should arrive from hospitals in digitized form so that the AI system can seamlessly extract required data without additional steps by the insurer.

An established claims management process. Structured procedures should be in place for reviewing claims and deciding whether or not to intervene

Structured, digitized documentation of results. Tracking the outcome of claims management activities is essential to provide an initial data basis for the AI system. In which cases did intervention take place, what form did it take place, and was it successful or not? Digital records should exist for at least the last two years, and ideally more.
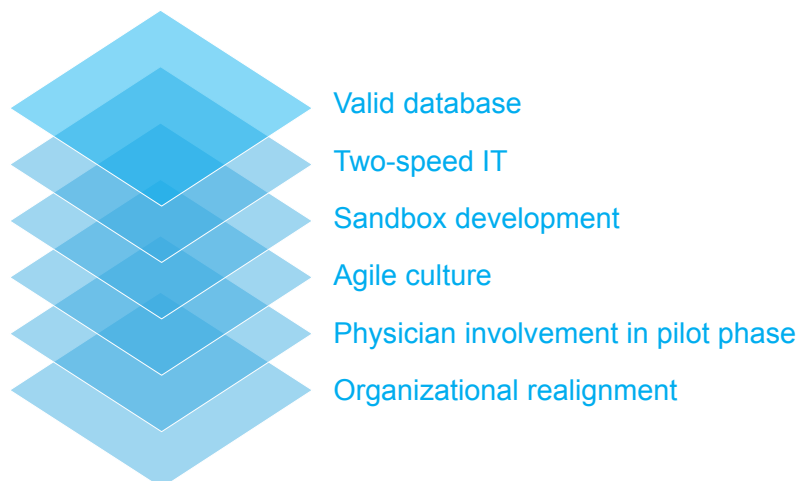
Insurers that do not yet fulfill these requirements are not ready to make the leap to AI-assisted claims management, but they can begin laying the groundwork for later success. And by keeping the goal of smart claims management in mind, they can design the needed systems and processes to provide the best possible basis for introducing AI when the time is right.

Determinants of success: getting implementation right

The development and testing of a suitable cognitive system is an important, but not the only, step on the path toward functioning AI-supported claims management. The right conditions must be in place to ensure that the system also works reliably in day-to-day operations and reduces the workload as planned. The factors that determine whether implementation is successful cover all levels of the insurance business – from the technical foundations to the work environment and team selection through to cultural transformation and changes in the organization.

Exhibit 3

6 determinants of a successful implementation

Valid database

Two-speed IT

Sandbox development

Agile culture

Physician involvement in pilot phase

Organizational realignment

SOURCE: McKinsey

Valid database. The benefits of a cognitive system for hospital claims management hinge on the size and quality of the database. These measures of data suitability determine how well an algorithm can be trained, how reliable its predictions are, and how fast it learns. A workable database generally encompasses several thousand data records with precise, consistent entries on the billing of individual cases (patient information, diagnoses, claims data) as well as related audit results.

Two-speed IT. Only rarely is it possible to adapt new technologies to legacy IT landscapes. Developing and implementing a cognitive system requires a new architecture that is separate from structures that have grown over time. Why? Applications are developed using modular concepts and steadily improved with continuous testing. This is best accomplished using a separate server that is detached from the rest of the organization's IT system.

Two-speed IT architecture is recommended for this reason. The existing foundation with its established operational systems operates at low speed, while the cognitive system "speedboat" accesses functions and data from legacy systems via selected interfaces only.

Development sandbox. A sandbox serves a similar purpose to the fast half of the two-speed AI architecture: it creates an environment in which the development team can test and enhance their systems separately from conventional structures. Specialists in a variety of disciplines (AI developers, data analysts, business users) work here together in a protected space that is technically and organizationally detached from other operations. This approach is essential in order to produce an innovative product that elevates the quality of hospital claims management instead of merely making one-off improvements.

Agile culture. Building an agile, self-learning system is only possible if those who develop and use it adopt an agile culture. Fast-learning teams continually check the value add of developed solutions, respond to users' experience, and iteratively modify their software. Advanced AI developers make optimizing modifications in short sprints lasting no more than two weeks – as fast progress is of the essence here.

Physician involvement in piloting. No later than the pilot phase, a medical expert team should be involved to give the new system's functionality a thorough check-up: For which claims is the algorithm recommending audits? Are the selection criteria all right? Is automated case selection integrated into the overall audit process? Do the administrative staff and auditors need to build up additional skills? Ideally, the medical expert team checks daily progress in the pilot phase, discusses claims flagged as unusual, and supports the audit process with targeted case training.

Organizational realignment. Integrating artificial intelligence into an established organization involves a great deal more than simply introducing a new technical tool. Working with cognitive systems affects workflows and procedures, roles and responsibilities, and judgments and decisions. To get the most out of AI deployment, the organization should be realigned to the new system early on. A well planned change program that manages the adjustments and involves all stakeholders in the process provides a suitable framework for creating the structures needed. More than that, it helps to win over employees, which is ultimately essential for success.

Benefits for health insurers –
greater efficiency, valid decisions

Embedding artificial intelligence in the process of hospital claims management offers multiple benefits at once, not just for insurers but also for patients, given the saving potential. In short, the shift away from claims management based on rigid rule books in favor of smart algorithms leads to greater efficiency and valid decisions – thus relieving the burden on all stakeholders and delivering savings.

Thanks to automated prioritization, administration staff no longer have to check every claim deemed unusual, but can instead focus on those cases that have the greatest reduction potential and the best prospects for successful intervention. A benchmarking analysis of a prioritization procedure based on historical test data shows the extent to which a cognitive system can predict this potential. The results show that the algorithm's hit rate closely approximates the ideal value – that is, the system correctly filters out almost all claims where the claim amount could be reduced (Exhibit 4).

Exhibit 4

AI-driven prediction models for identifying reduction potential nearly reach the ideal hit rate

Cases prioritized by cognitive system based on potential
(Test data)

Share of total reduction amount, percent
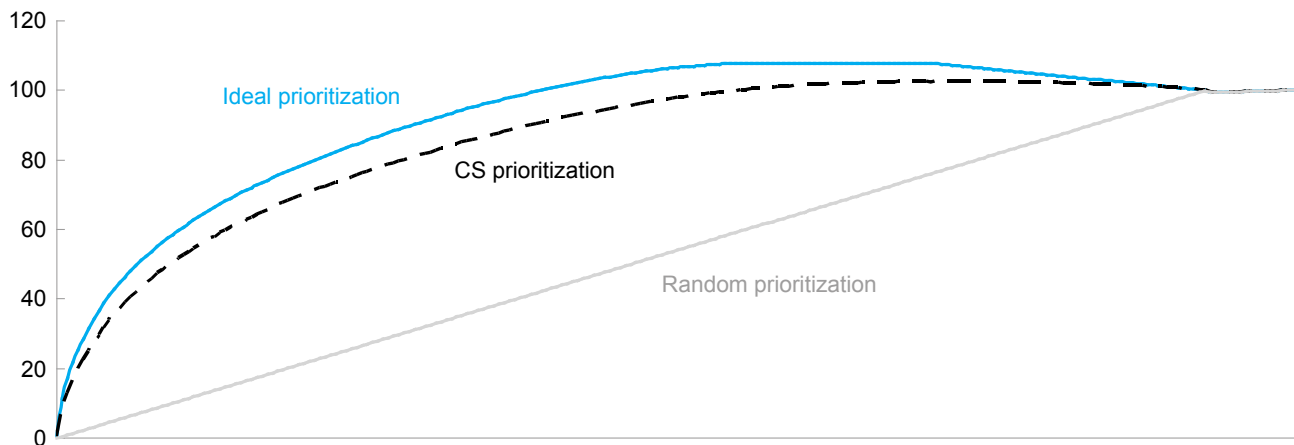
SOURCE: McKinsey

The cognitive system not only simplifies and accelerates the overall claims management procedure, it also enhances its quality: additional costs for redundant audit and rejection processes are eliminated, while available resources can be focused on the "right" cases, i.e., those that are truly relevant for audits. As a result, the system frees up capacity among administration staff and auditors so that they can correctly pinpoint reduction potential and properly prepare intervention cases – thus further increasing their prospects of success.

Moreover, the efficiency improvements possible with AI deliver measurable economic impact: at best, the savings currently achieved from successful claims reductions are in the range of 3 percent of the amount originally invoiced. An increase of one percentage point alone would afford German health insurers additional savings of around EUR 500 million each.

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Only a few health insurers in Germany have so far ventured into the new field of artificial intelligence. The reasons for this slow adoption vary: uncertainty about practical use cases, gaps in technology expertise within organizations, or a lack of transparency regarding the available data. However, any health insurer can benefit from the use of artificial intelligence – provided it establishes the requisite conditions. So it pays to start investing in suitable IT architecture now and create the agile framework needed to fully exploit the opportunities afforded by the new technologies.

Such opportunities extend beyond the field of hospital claims management discussed here. The potential spectrum of use cases for artificial intelligence is broad and varied. For instance, AI-based forecasting systems could be used for the early detection of high-risk patients or to project trends in other healthcare services provided by physicians, therapists, outpatient centers, pharmacists, or long-term care facilities.

One thing is certain: AI technologies are going to play a more prominent role in future healthcare management. Health insurers should thus take the opportunity to position themselves at the crest of the wave – and thereby maneuver their organizations into a good position from which to tackle the mounting challenges in healthcare.

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