Hyperautomation in payments

Harnessing AI to automate complexity at scale

White Paper

Digital Payments
for a Trusted World

Forewords

Prof. Dr. Ueli Rutishauser

Neuroscientist working on memory and neurotechnology, California Institute of Technology and Cedars-Sinai

One of the remarkable features of the human brain is its ability to form memories and use that repository of experience to detect patterns. This is what enables an expert to make accurate judgments often without explicitly knowing exactly why. How the brain achieves this feat is only now beginning to be understood. Translating the principles we discover from observing the brain into technology is revolutionizing how we build software and companies. This paper provides an excellent summary for the potential that this paradigm shift has for the financial industry. There is no doubt in my mind that a continued close interaction between neuroscience research and neuro-inspired technology will be what propels companies to be thought leaders in this industry.

Prof. Dr. Rafael Lalive

Professor of Economics at HEC Lausanne and member of the Swiss National Science Task Force on COVID-19

This paper comprehensively explains the essence of hyperautomation: the technology – great data and clever automation – coupled with the needs of people – explainability of AI recommendations and an organisation culture that embraces change. The report describes the state-of-the-art in AI and payment systems and illustrates the key takeaways with lessons learned at Wordline.

Executive Summary

The combination of an increasingly digitised world and the advancements in AI over the last decade now enables businesses to automate increasingly complex tasks. This strategic trend, known as hyperautomation, is driving cost savings and is expected to save 20-30% of human effort. It is also enabling entirely new business models and ways of working. In the wake of the COVID-19 crisis, which has introduced the essential digitisation of much of society and business, this trend will further accelerate.

Across the payments industry, we have seen AI bring more and more benefits. For example, one major card scheme is aiming to use it to slash card transaction declines. And at Worldline we have harnessed hyperautomation to boost the fight against fraud. Against a backdrop of retailers potentially losing $130 billion to online payment fraud by 2023, Worldline has already exploited AI to analyse billions of transactions and increase fraud prevention by up to 30%.

Strategic decision makers need to understand how to apply hyperautomation within their organisations to enhance efficiency, facilitate new business models and deliver highly personalised customer experiences. For many types of organisation, neglecting hyperautomation will lead to them being unable to compete in the market and becoming unappealing to consumers. Conversely, those who embrace this trend will thrive.

Fortunately, there are many readily available off-the-shelf AI-based components for image recognition, optical character recognition, natural language processing, and speech recognition, which can provide a relatively straightforward path to increasing the complexity of what can be automated.

However, organisations that achieve a high level of data maturity will be able to create even more value from hyperautomation. By understanding and leveraging data to train and deploy AI models into their business processes they will be able to use AI to make decisions, either by advising humans or by acting completely autonomously. Businesses using AI in this way will need to confront and conquer the challenges of accountability, acceptability, explainability and measurability.

Applying AI to automation is not only a technical challenge. Creating a “hyperautomation culture” requires a transformation which can only be achieved through strong leadership and effective organisational change management. Such a transformation requires that you:

- Understand your current **AI maturity**
- Analyse your existing **business processes**
- Close **skills gaps**
- Boost your **data maturity** and become a **data-aware organisation**
- Take **make-or-buy decisions**, identifying where to use third-party solutions and work with partners
- Decide where to focus your **internal research** efforts
- Integrate **explainability and ethics** from the start

In this paper, we share the combined experience of Worldline’s leading experts in automation, AI and related technologies. Building on our strategic research programme in this area, which has been running for over six years, we set out the primary technologies, techniques and use cases for hyperautomation in payments. Finally, we conclude with a roadmap to help you plan the journey towards hyperautomation for your business.

Contents

Introduction

Throughout the history of civilisation, the automation of repetitive manual tasks to boost efficiency and quality has been an unstoppable trend. In agriculture, harvesting 150 acres of grain with a scythe and threshing it by hand required 20 people working for 50 days[1]. Now, using a modern combine harvester, two people can do that amount in one day (a thousand-fold reduction in the manual effort needed). In manufacturing, the human effort required to build one car in the 1950s was about six months[2]. Now, this has been reduced to just four days[3] of manual labour.

More recently, as more and more physical activities have been digitised, these digital processes can be automated using software. Robotic Process Automation (RPA), which enables repetitive human interactions with software systems to be easily automated[4], is becoming mainstream, having been the fastest growing segment in the enterprise software market in 2018 and 2019[5]. RPA software provides a relatively low-cost route to basic automation by mimicking the actions of human operators (which means that it can be applied to legacy systems where significant technical debt has accumulated and no APIs are available).

From automation to hyperautomation

Automation has traditionally focussed on simple, repetitive tasks, replacing unskilled labour with machines and software code. Artificial Intelligence (AI) has always had the potential to make it feasible to automate tasks where, in the past, human involvement would still have been needed (such as extracting specific information from unstructured data). Now, the increased availability of computing power coupled with readily available state-of-the-art open-source algorithms has made this potential into a reality. This trend, of applying "advanced technologies, including artificial intelligence (AI) and machine learning (ML), to increasingly automate processes"[6] is known as "hyperautomation" and has been identified by Gartner as the number one strategic technology trend in 2020. Hyperautomation can be used to boost efficiency, and it can also enable entirely new ways of working and business models.

Hyperautomation can be used to boost efficiency, and it can also enable entirely new ways of working and business models

Boosting efficiency

In a survey of 750 business decision-makers, the top driver for AI adoption was reducing costs[7]. IBM estimates that they have achieved almost $1 billion in savings since 2011 by integrating artificial intelligence and other modernisation efforts into their HR processes[8]. In terms of future potential, the Deloitte Center for Government Insights predicts that AI could "free up 30 percent of the government workforce's time" and Autonomous Research estimate that, by 2030, traditional financial institutions could use AI to reduce costs by 22%[9].

New business models

Hyperautomation can also be used to enable entirely new ways of working and business models — as tasks can be performed faster on larger datasets than would have been possible through human effort alone. For example, YouTube's business model relies on millions of users uploading content to the platform. However, to respect the rights of copyright holders, YouTube must check every video for potential copyright infringement. With over 500 hours of video uploaded every minute, manually checking each clip would be prohibitively time consuming and expensive. Instead, their Content ID system uses AI to check for copyrighted content and either blocks it or uses paid-for advertising each time the clip is viewed to compensate the rights holder automatically[10]. The system even works when uploaders try various tricks to fool it, such as speeding up or slowing down material, changing the pitch of the audio, or cropping the picture.

Hyperautomation is also an enabler for the delivery of hyper-personalised services. A study conducted by Salesforce found that 83% of IT leaders report that AI is transforming customer engagement[11]. By way of example, 75% of Netflix users select films recommended by the company's AI algorithms[12]. In payments, the individualisation of risk scoring is already proving successful in allowing companies to offer, in real time, attractive and completely new payment methods tailored to individual consumers. By knowing the customer, and using the right algorithms, intentions can be predicted, and services adapted to spending patterns and individual risk.

Although hyperautomation can deliver many benefits, there are also questions about the broader implications for society. Whilst citizens may benefit from better, more personalised services that are delivered faster, hyperautomation (just like other forms of automation throughout history) will impact the nature of employment. Some existing jobs will disappear; other jobs, requiring different skillsets, will emerge.

83%

of IT leaders report that AI is transforming customer engagement

1 http://www.oecd.org/coronavirus/policy-responses/e-commerce-in-the-time-of-covid-19-3a2b78e8/

2 https://www.volkswagenag.com/en/group/history/chronicle/1950-1960.html

3 https://www.autocar.co.uk/car-news/features/building-40-new-cars-hour-inside-toyotas-burnaston-plant

4 https://www.gartner.com/en/information-technology/glossary/robotic-process-automation-rpa

5 https://www.gartner.com/en/documents/3985614/market-share-analysis-robotic-process-automation-worldwi

6 https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2020/

7 Algorithmia 2020 state of enterprise machine learning, accessed from: https://info.algorithmia.com/hubfs/2019/Whitepapers/The-State-of-Enterprise-ML-2020/Algorithmia_2020_State_of_Enterprise_ML.pdf?hsLang=en-us

8 https://fortune.com/2020/01/24/ai-ibm-human-resources/

9 https://thefinancialbrand.com/72653/artificial-intelligence-trends-banking-industry/

10 https://www.fastcompany.com/4013603/youtube-is-using-ai-to-police-copyright-to-the-tune-of-2-billion-in-payouts

11 Salesforce Enterprise Technology Trends report, accessed from https://www.salesforce.com/research/market/

12 https://www.forbes.com/sites/louiscolumbus/2020/01/19/roundup-of-machine-learning-forecasts-and-market-estimates-2020/#33044525c020

Accelerated digitisation

In our previous paper "The World After COVID-19: Adapting your business now for the new normal in payments"[13] we explained how the global pandemic catalysed a shift of "mindsets in society and business that will outlive the current emergency." In particular, there has been an acceleration of digitisation which we believe will lead to a corresponding acceleration in hyperautomation. With more tasks completed digitally, there will be more opportunities to apply AI (such as chatbots and digital identification). Simultaneously, there will be more data available to train and improve AI algorithms to fulfil these needs.

As consumers access more and more products and services digitally, they are developing an "everything now" mindset: expecting that anything they need is available at the swipe of a screen. With an increasing amount of activities performed online, the risk of digital fraud is greater, and the need to rapidly differentiate fraudulent actions from legitimate ones without impeding the user experience is becoming ever more critical. For example, as the eCommerce industry continues to grow rapidly, both payment fraud and false chargebacks are on the rise. Juniper Research estimates that by 2023 retailers could lose about $130 billion due to fraudulent eCommerce transactions[14]. And this challenge is not only relevant for traditional card payments. With the use of instant payments expected to increase, the European Commission's Retail Payments Strategy for the EU has identified that payment service providers must have in place real-time tools for detecting and preventing potential fraud, money laundering and terrorist financing.

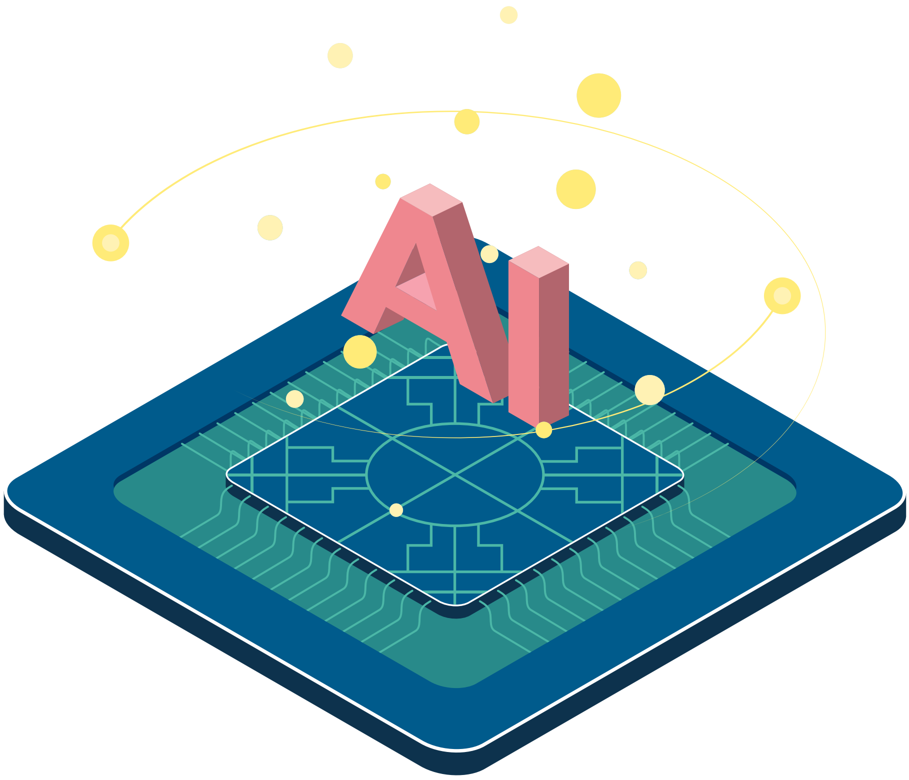
Hyperautomation for survival

Today, organisations that are not applying hyperautomation to their products or services are, at best, missing out on opportunities to reduce costs and increase revenues. At worst, if their competitors make this move first, they may struggle to compete, fail to engage their customers, or even become irrelevant in the market.

Despite these pressing needs, many organisations today do not have the required capability to shift to hyperautomation. They may lack the needed automation culture, data maturity, or knowledge of AI that is necessary to identify suitable use cases and implement them quickly. They may be faced with legacy IT systems based on old technologies upon which it is difficult to layer AI-based automation.

At Worldline, our strategic research programme in partnership with eight European laboratories, which has been running for over six years, has determined how AI can be applied within the payments industry. Our engineers have worked side-by-side with academics to conduct numerous research studies and have published scientific papers that have become established reference points in the field of fraud detection. We have built numerous proofs of concept. Furthermore, we have also applied AI in our production environments, analysing billions of transactions and achieving measurably higher rates of fraud detection.

In this paper, we share our experiences and the lessons learned to help you understand how AI can be applied to automation, the types of use cases we see within payments, and the main challenges involved. At the end of this paper, we provide practical recommendations to help you take the next steps on your journey towards harnessing the power of AI inside your enterprise.



13 https://worldline.com/content/dam/worldline/documents/publications/whitepapers/the-world-after-covid19-white-paper.pdf
14 https://www.ravelin.com/insights/online-payment-fraud

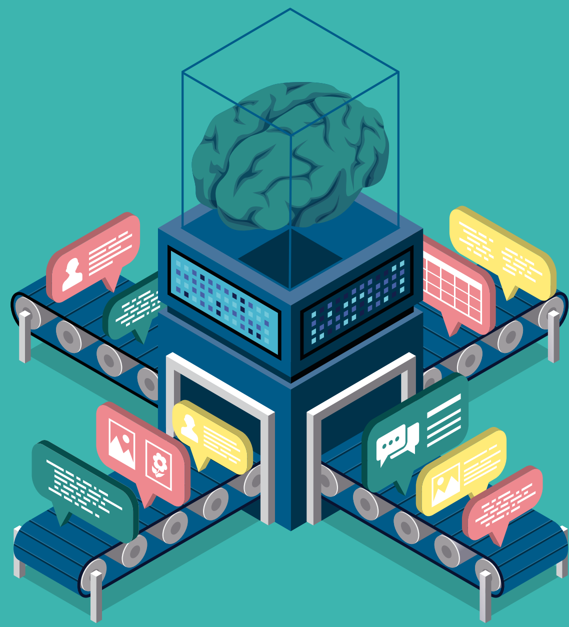
Automation with AI

Why apply AI to automation?

It is possible to develop automation using traditional software coding methods. Where the task to be automated can be easily described as triggers and actions (like “if x, do y”), then writing code to automate the task is a perfectly reasonable approach. However, sometimes it can be difficult or even impossible to write rules to automate a task because either:

- It is too difficult to codify the process (e.g. trying to write the logic for “are these images similar?” by looking at one pixel at a time)
- Codification of the process is not possible because the required logic changes over time and consequently is unknown at the outset (e.g. new, previously unencountered fraud behaviours)
- It is possible to codify the task, but the resulting algorithm is too inefficient to be useful (e.g. consumes too much power or takes too long)15

AI can provide solutions to these challenges and so provide a lever to increase the complexity and scale of what can be automated, and how autonomous that automation can be[16].



RPA as a first-step

At Worldline we use RPA to automate hundreds of internal processes. Whilst RPA is sometimes considered to be “dumb automation” due to its focus on automating simplistic tasks, we have still found that it brings benefits beyond the immediate efficiency gains. In particular, we have found that implementing RPA helps us to:

- Demonstrate to people the benefits of automating repetitive work (e.g. allowing them to focus on more critical or high value work)
- Gain knowledge about the organisational and structural setup needed for the viability of AI
- Investigate the operational improvements necessary for AI implementation.

The rise of AI for automation

Although we have so far referred only to AI, it is worth noting that much of the increased interest in AI over the last decade is focussed on Deep Learning (an advanced subset of machine learning based on the use of large neural networks). Deep Learning has become more relevant due to the increase in the availability of computing power, data to train neural networks, and new deep learning frameworks and architectures (see Figure 1). Deep Learning uses algorithms such as Convolutional Neural Networks, Recurrent Neural Networks, Deep Q-Learning, Generative Adversarial Networks, You Only Look Once (YOLO) Neural Networks, and Transformers. These algorithms provide improved capabilities in fields such as image classification, image recognition, natural language understanding, prediction, segmentation, recommendations and anomaly detection.

The advent of the graphical processing unit (GPU) co-processor enabled machine learning and deep learning to run on relatively standard hardware. Recently, companies such as Tesla, Google and Facebook have started to create their own processors for artificial intelligence applications[17]. Open source frameworks such as TensorFlow and PyTorch have reduced the barriers to entry even further by simplifying the software frameworks for training and running AI models.

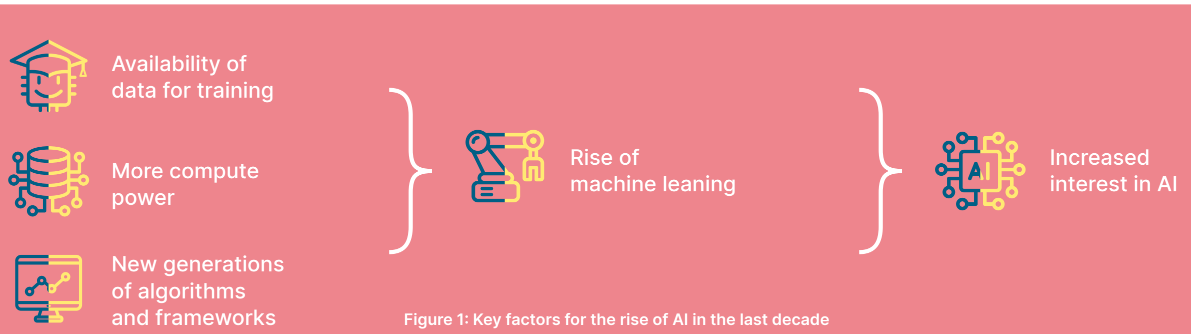


Figure 1: Key factors for the rise of AI in the last decade

15 Note that although AI algorithms may be efficient to run, ML models do nonetheless require significant compute power for training-usually a task performed using large GPU farms
16 Sometimes the traditional approach to coding in an “if x, do y” manner is referred to as Software 1.0, whereas the approach of using data sets to train an AI model is referred to as Software 2.0
17 https://www.linkedin.com/pulse/apple-arming-itself-urs-gubser/

Specialised hardware, such as the Tensor Processing Unit or "TPU"[18], is used by some organisations to run these frameworks at massive scale today. Cloud services have reduced the entry barrier further by having pre-trained models and vast data sets available via APIs that can be run with just a few lines of code. What was once the realm of a few academics is now available to all.

TensorFlow and PyTorch can run on off-the-shelf computers with even relatively modest GPUs (and they are also available as-a-service or in "lite" versions for deployment to phones, payment terminals, and IoT devices). Open source data sets are available for anything from COVID-19 research[19] to categorised sets of toy minifigures[20] to pre-train models before companies even have to consider using their own datasets.

However, despite all of this progress in recent years, it is essential to remember that AI is not a panacea. There are still many tasks that can be better implemented using traditional code. What's more, the knowledge and skills required to master AI are not so common as for traditional programming. A lack of experience, coupled with the fact that many AI implementations cannot be tested or reviewed in the way that traditional code can, brings risks. It is therefore crucial that organisations can identify the types of use cases where AI is beneficial, and those where it is not.

How to apply AI to automation

Our experience shows that AI can be applied to automation in two primary ways (as shown in Figure 2). The first way is to apply AI as a "perception layer" which can augment "simple automation" to make it applicable in a broader range of scenarios. The second way is using AI to make decisions, either by advising humans or acting autonomously. As we move from simple automation towards AI for decision making, the complexity of what can be automated increases; however, the maturity of available solutions and techniques for implementing this automation is greater for simple automation than it is for the most advanced forms of hyperautomation.

As organisations seek to use AI for decision making, they will also need to ensure they understand where to source AI algorithms (internally or externally) and how and when data is required in order to implement AI solutions effectively. In particular, they will need to recognise the distinction between specific data, such as customer, service and self-generated data, versus third party external data (structured and unstructured). There are drawbacks and opportunities for using specific and external data in combination with in-house or outsourced algorithms. Using third party data may be a way to get a large volume of data quickly, although it may also come with a financial cost and less control over its quality.

In the following sections we cover the use of AI for the perception layer, the requirement for organisational data-awareness, and the application of AI for decision making.

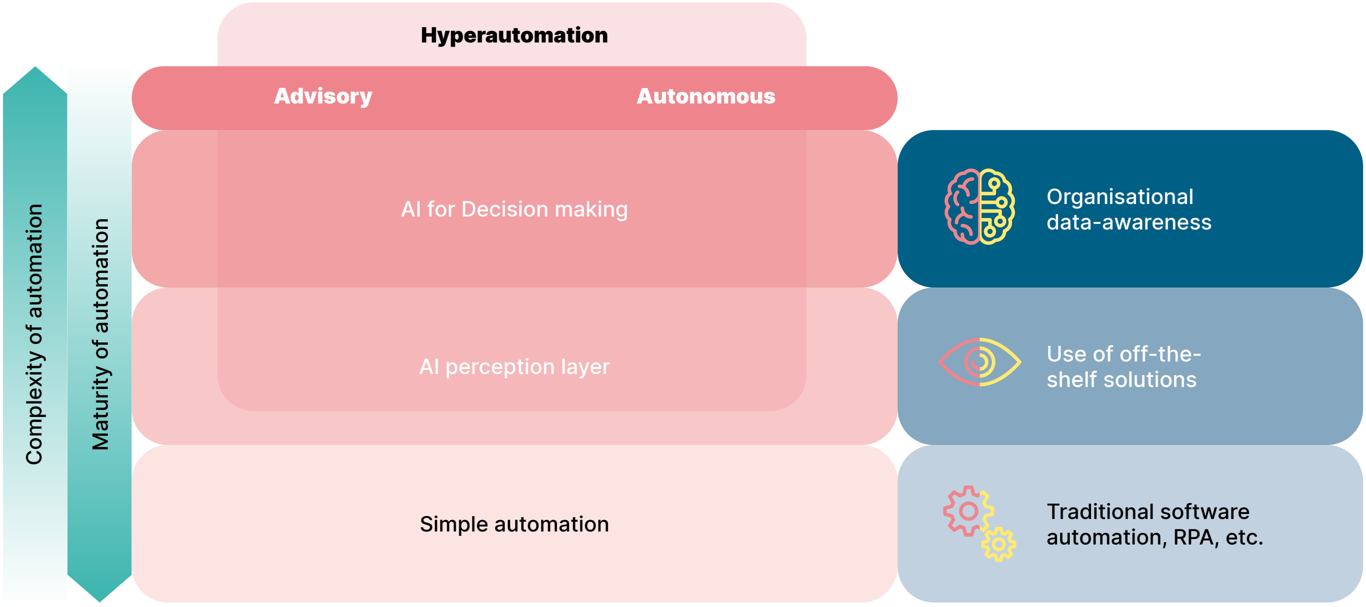


Figure 2: How AI can be applied to automation

18 https://cloud.google.com/tpu/docs/tpus?hl=en
19 https://www.kaggle.com/allen-institute-for-ai/CORD-19-research-challenge

AI as a perception layer

As shown in Figure 3, four widely applicable uses of AI as a perception layer are image recognition, Optical Character Recognition (OCR), speech recognition and Natural Language Processing (NLP). This section provides some examples of use cases for each one, as well as describing some of the readily available off-the-shelf solutions for implementing them.

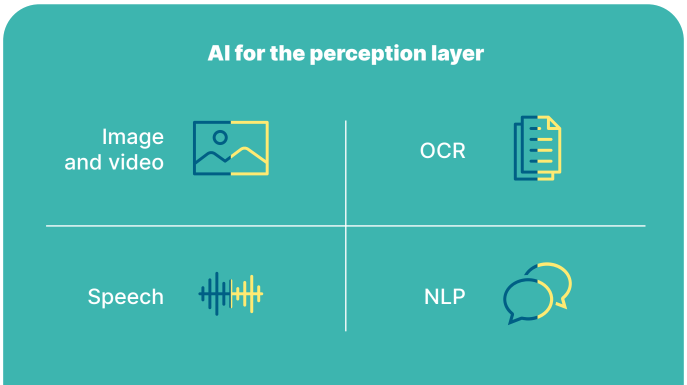


Figure 3: AI for the perception layer

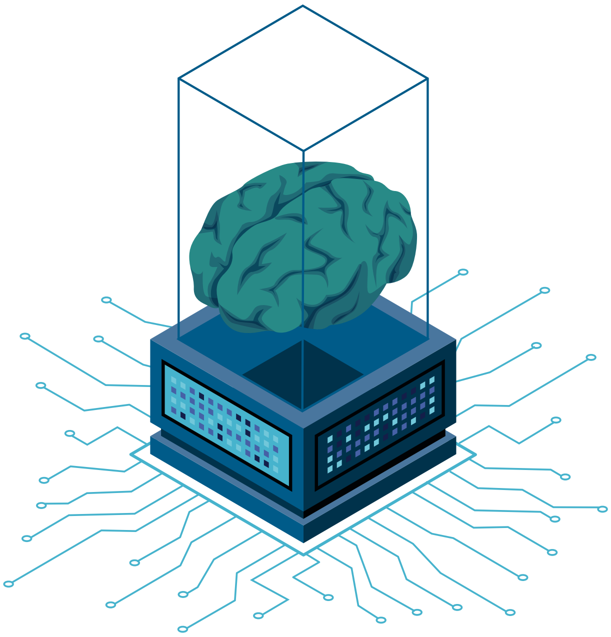


Image recognition

AI algorithms can be used to extract information from images (including video). Typically, machine learning algorithms are trained using a dataset of labelled images. A well-known example is the tagging of people in photos uploaded to Facebook. To begin with, users had to manually tag people in photos. That manual tagging was then used to train the AI algorithms which can now suggest who is in a photo automatically. Another well-known use case in medicine is the identification of potential tumours in radiology. Worldline recently developed a proof of concept showing that radiologist levels of performance could be achieved using AI, including providing a visual indication of where in the scan the anomaly was detected.

Image recognition can also support biometric authentication. One example that we have investigated at Worldline is the use of face identification in public transport validators in Latin America, to prevent people from using concessionary travel passes that belong to someone else.

Image recognition is also an enabler for Augmented Reality (AR) where it is used to analyse surroundings in real time in order to superimpose information onto them. Worldline has been investigating use cases where such technology can provide “virtual assistants”, for example to help people diagnose and fix hardware issues themselves without requiring an engineer visit.

Related to image recognition is the analysis of video. We mentioned earlier how YouTube uses AI to detect copyright material, and many other use cases exist, from Automatic Number Plate Recognition (ANPR) systems to control car parks through to automated monitoring of CCTV for suspicious behaviour.

Optical Character Recognition

Optical Character Recognition (OCR) is a specific branch of image recognition, focused on interpreting printed or handwritten text. This technology can be applied where one or more inputs to a process consist of paper-based documents.

A particular use case that we see within payments is for Know Your Customer (KYC) and compliance with Anti Money Laundering (AML) regulations. Here document verification of online customers against official ID documents such as a national ID card, passport or driving license can be done in near real time by AI-powered Optical Character Recognition (OCR) technology. At Worldline, we are implementing OCR[21] for automating the verification of ID cards in our merchant onboarding and, in our Financial Services Lab, we delivered a proof of concept which used OCR to implement multifactor passport fraud recognition[22].

We are implementing **OCR** for automating the verification of id cards in our merchant onboarding

21 Using IDnow.io’s AutoIdent

22 This involved the use of OCR and image recognition with a multi-factor adaptive algorithm to determine the likelihood that a passport was fraudulent, by extracting the information (e.g. photo, name, age, gender, nationality, number) and cross-validating it.

Speech recognition

Just as OCR can be used when a paper-based document is an input to a process, speech recognition can be used with the human voice, both to authenticate a user and to interpret the words they are speaking.

AI models have recently been able to **surpass human performance** on public benchmarks for many Natural Language Processing (NLP) tasks

Voice authentication first requires an authenticated person to repeat a specific phrase several times. From this an "audio fingerprint" is created and stored. For future interactions, the user can simply say this phrase once to authenticate themselves.

Understanding which words have been spoken by a user can be used in conjunction with Natural Language Processing (another branch of AI) to interpret verbal requests and take actions accordingly. A natural use case for this is a helpdesk, where simple ticket raising activities traditionally performed by a human operator can be performed automatically using AI technology.

Natural Language Processing

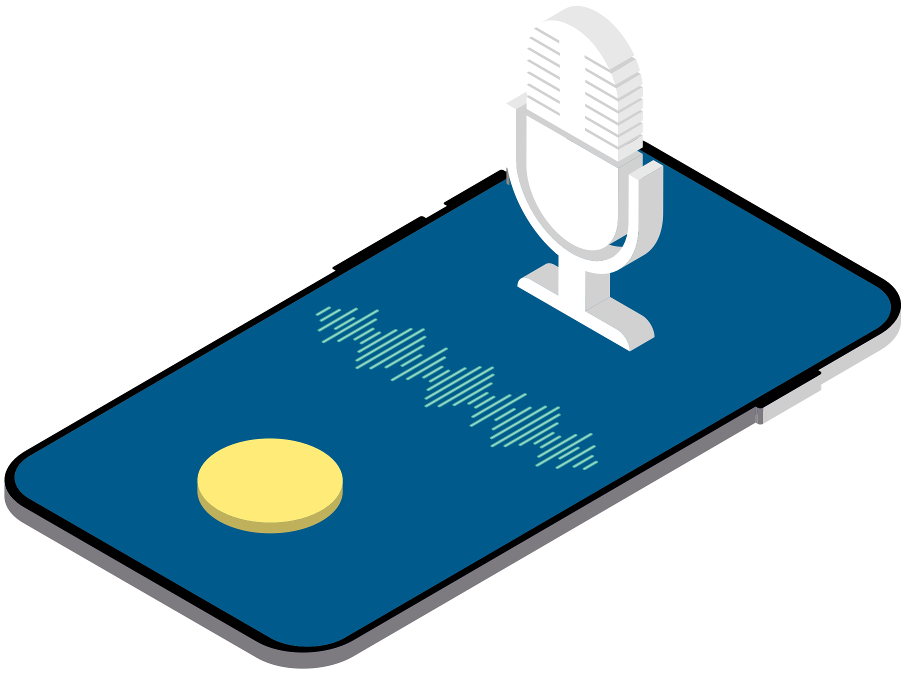
Natural Language Processing (NLP) enables people to interact with computers in a similar way to how they communicate with humans. With several disruptive innovations over the past five years (for example, the BERT language model[23]), AI models have recently been able to surpass human performance on public benchmarks for many NLP tasks such as reading comprehension or text classification, especially where there are no subtleties such as double meanings or irony. And these algorithms are continuing to improve. Indeed, at Worldline, we created our own enhancements to BERT which resulted in improved accuracy and a ten-fold increase in speed. One example of where Worldline has applied NLP is in our Contact platform to respond automatically to text and voice queries using chatbots. Not only does this avoid the need for human agents to respond to those queries, it also means that customers receive immediate responses 24/7. Our application of NLP means that we can understand the customer's intent, find the information they need, personalise its presentation based on the conversational context, and analyse the level of satisfaction/ sentiment that the user has with the interaction. Similarly, within our Trusted Interaction product, we have applied NLP to understand why a client is contacting their bank advisor by email and then respond automatically[24].

Using off-the-shelf perception layers

Most best-in-class perception layers use similar architectures and algorithms. Implementing one from scratch that can reach a high level of performance requires advanced, time-consuming research. This means that the best approach for many companies will be to use existing third-party high-level components.For example, when we develop a chatbot for integration into one of our products, we reuse existing speech-to-text and NLP technology. That does not mean that no AI expertise is required, rather that the expertise needed is to set up, fine-tune and integrate the off-the-shelf component (rather than developing it from scratch).

The recent **evolution of cloud offers has disrupted** this landscape

The recent evolution of cloud offers has disrupted this landscape. The three leading public cloud providers are now offering AI services at different levels of abstraction, considerably reducing the required implementation effort. For example, a chatbot solution could be developed entirely using the tools provided by platforms such as Amazon Lex or Google Dialogflow.



23 https://en.wikipedia.org/wiki/BERT_(language_model)

24 https://equensworldline.com/en/home/solutions/digital-banking/trusted-interactions.html

Building a data-aware organisation

In the previous section, we discussed the use of AI as a perception layer to broaden the applicability of simple automation. We noted that, for the purpose of providing a perception layer, there are many available off-the-shelf solutions. In these cases, organisations will generally not need to use their own (or their customers') data to train them; the models will be pre-trained using datasets that have already been collected.

We also described earlier that the recent growth in AI has been driven by advances in machine learning. We have also seen that these ML algorithms require training and that, for many of these algorithms, large, high-quality datasets are required for this training[25]. These datasets can take many forms, such as images, audio, electronic transactions or system logs.

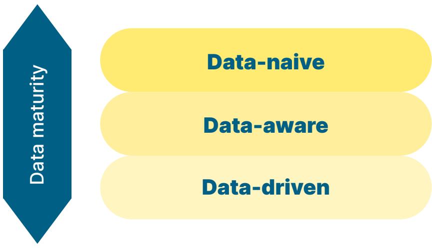


Figure 4: The data maturity spectrum

As shown in Figure 4, the data maturity of an organisation will be somewhere along a spectrum from "data-naive" to "data-driven". Data-naive organisations will typically have little or no understanding of the data they own or could access, nor will they have a strategy in place for deriving value from it. At the other end of the spectrum, a data-driven organisation will use data as a core part of their strategy. Not only will they have a clear view of what data they have and could obtain, but they will also have a clear strategy for how to derive value from it and they will use data as the foundation for all their decision making.

In the middle of the spectrum are those organisations that are data-aware: they collect data and make it accessible, actively manage issues of ownership and regulatory compliance, have policies for data sharing with other organisations, and the capability (in terms of infrastructure and skills) to ingest, process and analyse data.

When an organisation wishes to use AI for decision making within their core business, they will usually have to train models themselves, using their own data, data from third parties, data from their customers, or even a combination of all three.

For an organisation to leverage AI for **decision making** within its core business, there is a prerequisite for the organisation to be data-aware

Therefore, for an organisation to leverage AI for decision making within its core business, they must at least be data-aware. And just as data-awareness is a pre-requisite to using AI for decision making, so the use of AI for decision making is one of the enablers for becoming data-driven. Data accessibility and security

Data accessibility and security

Large players in every industry have grown over time and, as a result, their business system architectures have expanded as well; this leads to a situation where they keep data in silos and accessing data becomes increasingly challenging. There is often no data governance in place — in other words, there is a lack of clarity about who can or should extract which data and how they can or should use it. Furthermore, legacy systems have often not been engineered to provide access to data in such a way that it can be readily used for AI. Sometimes the solution is to introduce a data intermediary (such as operational data stores or data lakes). In these cases, a security framework also needs to be put in place to ensure that access to data is controlled (and data breaches avoided).

As shown in Figure 5, organisations faced with this challenge can tackle it using a bottom-up or a top-down approach.

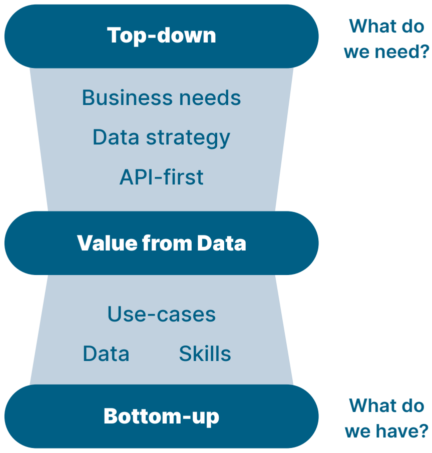
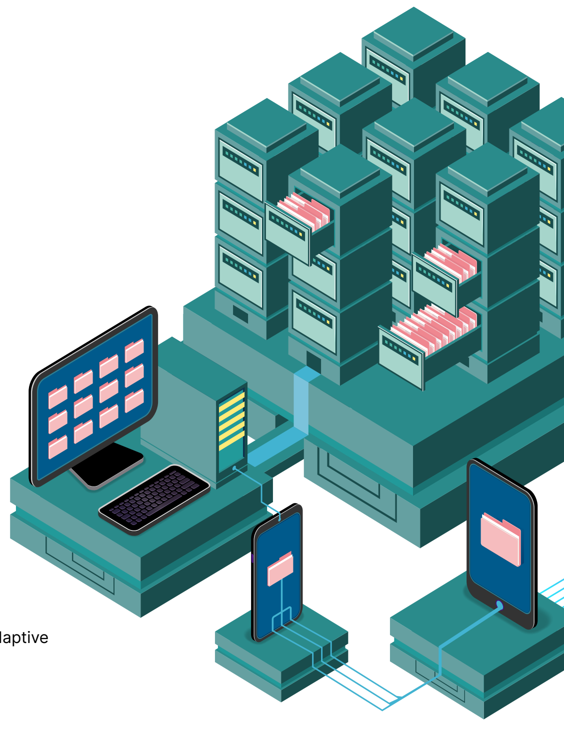


Figure 5: Top-down and bottom-up approaches to data

A bottom-up approach starts by asking the question: what do we have? Organisations look to use the data and skills they already possess and then identify potential use cases or problems that they can solve with them. This approach is known as "purposefully driven data strategies"[26] and it's a step-by-step method that can help to pave the way for more sophisticated data analytics solutions. It also starts to build up a data inventory that enhances the data-awareness of the organisation.



25 Note: ML models can either be pre-trained (in which case all data to train the model is required up-front) or can be adaptive (learning continuously to improve their own performance as data is processed). Both approaches can be combined (pre-training as a starting point, followed by adaptive learning).

26 https://store.hbr.org/product/10-steps-to-creating-a-data-driven-culture/H05DLG

A top-down approach starts by asking the question: what do we need? This only works if the company has a strong vision for how they can use data and where they should invest. Jeff Bezos famously mandated that every team at Amazon expose their data via interfaces that could be accessed internally and externally[27]; this would typically involve the creation or formation of a central data organisation with the task of understanding what the business needs, developing a data strategy, and driving forward an API-first approach. Teams can then solve sophisticated challenges by building the necessary connections to the data sources, extracting the relevant data and implementing solutions.

Ownership and regulatory control

Consumers expect that they can trust organisations to manage their data carefully and use it only in ways that they consent to. Increasingly, companies seek to demonstrate this as a core value and an integral part of their brand. However, if this trust is breached, companies can face a significant backlash: losing users and facing investigation by authorities[28]. In many regions, consumers are protected by legislation (for example GDPR in Europe) which can place strict conditions on how data is used, managed and retained. Data anonymisation and aggregation can sometimes be used to address these concerns, but still great care is required. For example, sometimes combining anonymised datasets makes them less anonymous, or aggregating data in certain ways can still make it possible to identify individuals.

All parties concerned need to see the **sharing of data as a win-win**

Although legislation like GDPR does not govern data belonging to organisations, clearly the consent of the organisation owning it will be required before it can be used. As such, all parties concerned need to see the sharing of data as a win-win (typically one organisation receives a better service at a lower cost in exchange for sharing the data needed to train the AI models). A recent example where data sharing occurred for the overall benefit of society was when Worldline supported the "Monitoring Consumption Switzerland" project, which used anonymised and aggregated payment data to enable changes in consumer behaviour to be analysed. The project makes extensive use of data visualisations and results are shared as live dashboards on Tableau Public. The special feature of the project is the speed of data analysis which continues to provide valuable information for political decision makers during the COVID-19 crisis[29]. In a worldwide first, it has shown that in this region the requirement to wear face masks has a negligible impact on retail revenues. The conclusion: it is not necessary to compromise between the public health benefits of masks and the economic benefits of consumer spending[30].

We have also found that full and unfettered access to datasets is not always required in order to apply AI. Indeed, some ML models do not require pre-training at all and can instead learn from data once they are running. But even where pre-training is needed, this does not mean that ownership of the data is essential.

Full and unfettered access to datasets is not **always required** in order to apply AI

We can draw an analogy between human learning and machine learning: staff working for a company expand their skills and knowledge as they work on tasks in order to provide services to their clients. Whilst it would usually be unethical and unlawful for those employees to directly share information received from one client with another, it is quite acceptable (even desirable) for them to apply the general skills and knowledge that they have gained from individual cases to increase the quality and efficiency of their work for all customers. Applied to AI therefore, having full ownership rights over any one dataset is not so important; what matters is having the right to use the AI models trained with that data to provide improved services to other customers.

This training could even be performed without direct access to the datasets at all. It is possible to provide a bootstrap model to a client for them to train using their data. They can then return the trained model, without sharing the data that was used to train it.

Another approach is known as "Federated Learning" where machine learning models are trained across multiple decentralised edge devices (e.g. IoT devices, mobile phones, etc) holding local data samples, without exchanging them. This approach enables multiple actors to use a common machine learning model without sharing data, thus addressing issues around data privacy and data access rights.

Monitoring Consumption Switzerland is an exciting initiative that demonstrates how sharing and visualising data can shed light on a highly relevant current policy debate: How is COVID-19 affecting our consumption and payment behaviour?

Prof. Dr. Martin Brown
Professor of Banking at the University of St. Gallen, Switzerland

Data sharing and industry data platforms

The European Union has recognised that one way to accelerate the application of AI is to facilitate the sharing and combining of datasets from multiple players in the same industry (or across industries). With this in mind, they have launched the GAIA-X initiative to facilitate the secure and trusted interchange of data between multiple organisations[31]. Increasingly, governments, not-for-profit organisations and commercial businesses are exposing more data. Two examples of this include opendata.swiss[32] (in Switzerland) and Transport for London[33] (in the UK). The automotive industry has also developed connected vehicle data sharing platforms, enabling new services such as autonomous payment at gas stations and parking garages. Connected vehicle data also allows insurers to create pay-how-you-drive insurance services.

---

26 https://store.hbr.org/product/10-steps-to-creating-a-data-driven-culture/H05DLG
27 https://www.cio.com/article/3218667/have-you-had-your-bezos-moment-what-you-can-learn-from-amazon.html
28 https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html
29 https://www.srf.ch/news/schweiz/sommer-und-corona-erfolgreicher-bergtourismus-dank-schweizer-touristen
30 https://www.nzz.ch/wirtschaft/coronavirus-maskenpflicht-geringe-einbussen-fuer-geschaefte-ld.1576918
31 https://www.data-infrastructure.eu/GAIAX/Navigation/EN/Home/home.html
32 https://opendata.swiss/en/
33 https://tfl.gov.uk/info-for/open-data-users/

We expect that we will see **more platforms emerge** to enable data exchange between businesses

In the B2C space, we have seen many single and multi-sided platforms emerge where one of the commodities being exchanged is data (e.g. the well-known example of sharing information about yourself to enable targeted advertising in exchange for free access to a service). Although still in their infancy, we expect that we will see more platforms emerge to enable data exchange between businesses, with one of the main drivers being the increasing thirst for data to train AI models. At Worldline we have created a Data Traceability Platform based on blockchain technology which can trace which dataset comes from which company (to enable trusted data sharing) and can allow the data providers to keep control over the data they have shared[34].

Generating valuable insights from data

Having explained that increasing an organisation's level of data-awareness requires access to data, we will now briefly describe how this data can be converted to valuable insights. Data will typically go through a chain of processing and analysis in order to extract value from it and to develop new data-driven products. For example, from a shopping-basket dataset of a retailer, first the content can be analysed to provide detailed information about customer buying habits, then from this a product recommendation tool or a sales predictor for stock management could be developed.

To efficiently move from raw data to concrete AI capabilities, the data goes through a complete lifecycle: ingestion, pre-processing, storage, computation and visualisation (see Figure 6). The three first steps are required to load and make the data available for processing and visualisation.

Recruiting people with these highly in-demand skills and retaining them is a **key challenge for creating and maintaining data-awareness** within a company

The two last steps are the ones where the value is generated. They are where data is processed to train AI models, and they are where data is visualised to show stakeholders information relevant to their business.

Data ingestion, data pre-processing, data storage, computation, visualization, analysis: the AI data life cycle is a thorny endeavour, particularly because value creation takes only place in the last step. This is as true for business as it is in research. The more unstructured the data, such as in my textual analysis of financial reports, the greater the challenge. I think these steps couldn't be better summarized than in Figure 6.

Prof. Dr. Matthias Fengler
Professor of Econometrics, University of St. Gallen, Switzerland

Implementing the data lifecycle requires the right technology platforms and appropriately skilled people:

Platforms will typically be comprised of big data products that can store and process huge volumes of data; data labs that will be used for data analysis, prototyping and experimentation; and data visualisation tools. All these need large amounts of computing resources that can either be provided by clusters of dedicated physical servers or in the cloud.

Figure 6: The data lifecycle

In terms of the skills needed, different profiles are required at different stages: data engineers, business intelligence experts, ML engineers and data scientists. Furthermore, all of these profiles must collaborate very closely with software developers and business domain experts. Recruiting people with these highly in-demand skills and retaining them is a significant challenge for creating and maintaining data-awareness within a company.

A driving motivation for making data available and accessible is to create high-level summaries of business-relevant KPIs. But the credibility of such KPIs is only as sound as the logic used to create them. This is where exploratory data visualisations come into play. Raw data often describes individual transactions or events. Some of these are irrelevant for calculating a given KPI, and others need to be combined in order to describe a single business-relevant metric. Exploring the data visually is the quickest and most reliable way to establish how data records need to be combined to accurately represent business processes. We use Business Intelligence (BI) tools such as Tableau for this purpose because it hides the technical complexity of creating charts and experienced users can create new visuals as quickly as they can imagine them.

Exploratory data visualisations and specialised techniques like Process Mining often reveal gaps. Several pre-processing steps are required to transform raw data into a data model that enables us to map automated system actions and technical actions by our employees onto understandable steps in processes that generate value for our stakeholders.

Customers appreciate data storytelling when it's targeted to a business goal and enables them to make critical decisions with confidence. Without the exploratory phase and data pre-processing, such charts can still be created, but they cannot be trusted. Having the capability to link charts interactively and refresh them dynamically not only brings more current information but also maintains our confidence in the correctness of the numbers and quickly alerts us to areas where the data model needs updating. Working incrementally in this fashion is key to enabling decision makers to ask and answer their own questions.

34 https://worldline.com/content/dam/worldline/documents/publications/position-papers/blockchain-en.pdf

AI for decision making

Having considered how a company can become more data-aware, let's now look at how that data can be utilised to enable AI for decision making.

In the transition from the lab into real-world application, fundamental challenges arise when using AI for decision making:

If an AI algorithm makes a decision, who is legally accountable for that decision and the consequences that arise? A commonly discussed example is if an autonomous vehicle has an accident. But many other examples exist in the world of finance and payments: from incorrectly assessing a credit risk through to paying out a fraudulent insurance claim.

How reliable does an AI algorithm have to be before its use is acceptable? Usually, AI is expected to perform orders of magnitude more reliably than humans doing the same task. For example, current research suggests that autonomous vehicles need to be 100 times safer than those driven by humans for their use to be publicly acceptable[35]. Similarly, if there is a bias in the data used to train ML algorithms, then that bias will be present in the decisions that they make. It is clearly unacceptable for a computer algorithm to discriminate (for example based on gender or race), yet research suggests that the use of machine learning algorithms (rather than traditional logic) for assessing the probability of a loan default provides greater benefits for majority groups (e.g. White non-Hispanic) than for minority groups (Black and Hispanic)[36]. Such discrimination is not only unacceptable but also unlawful, with companies facing investigation when their algorithms appear to display bias, as illustrated by a recent example where the credit limit offered to a husband was twenty times higher than that offered to his wife[37].

How can a decision made by AI be explained?

An ML algorithm will make a decision based on how it has been trained from a dataset, but it is often not at all straightforward to understand why and how the model reached its conclusion.

Several techniques can address this challenge. One is to use AI to generate rules (such as a process flow) that humans can understand. For example, at Worldline we have developed an "Auto Rule Generator" which uses AI to create new rules every day for fraud detection by analysing transactions. In this way, humans can understand the rules (i.e. they are explainable) and the reason for blocking any individual transaction is obvious. We have also developed a proof of concept where we applied different AI explainability techniques (PDP Plots, LIME and Anchor) to understand an AI model's decisions for loan default prediction. Figure 7 shows an example where the main factors predicting a 94% chance of a loan default are the number of delinquent credit lines (DELINQ) and recent credit inquiries (NINQ).

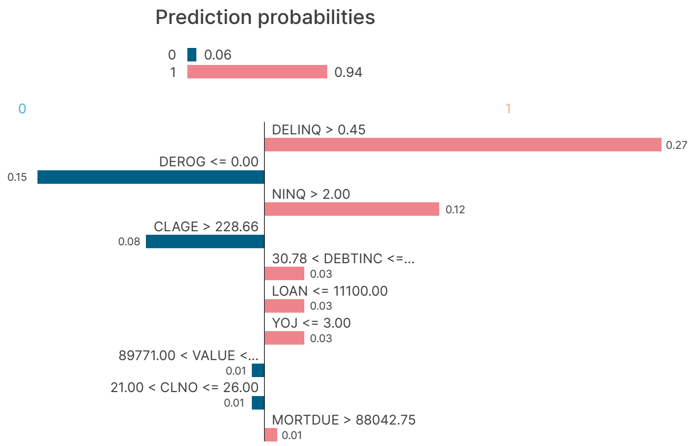


Figure 7: Example of a LIME explanation for Extremely Randomized Trees model with a Positive sample

In the case of fraud detection, AI achieved between **20%** and **30%** more detection capability

How can the performance of an AI algorithm be measured?

The nature of AI algorithms (where there is no traditional code describing the logic behind its decisions) means that it is not always easy to guarantee or measure whether an AI algorithm is outperforming human or existing software-based decision making. We have researched ways of measuring the value added through AI.

35 https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety24 https://equensworldline.com/en/home/solutions/digital-banking/trusted-interactions.html

36 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3072038

37 https://www.bbc.co.uk/news/business-50365609

In the case of fraud detection, we compared, using standard metrics, the results achieved both with and without AI and found that AI achieved between 20% and 30% more detection capability. This equates to between €25-35 million of additional fraud prevented in 2019 for our clients in Belgium and Germany alone.

Selecting relevant metrics for performance measurement is a challenge. For example, common fraud prevention KPIs in contracts (i.e. precision, recall) can be influenced by uncontrollable factors (e.g. the number of fraud attempts). Through a combination of theoretical and empirical analysis, we designed new types of model evaluation metrics that are "calibrated" and enable a better understanding of our detection system's behaviour and more solid contractual terms.

Advisory AI

As we have seen, using AI for decision making has challenges related to accountability, acceptability, explainability, and measurability. Many of these challenges are reduced when AI is used to provide recommendations or advice to a human (who will then take the final decision). In the paragraphs that follow, we will cover some of the main use cases of "advisory AI" before we then move on to examining some use cases where AI can act autonomously, making decisions and taking actions without any human intervention.

A classic use of advisory AI is providing product recommendations. As part of our contribution to the European Commission funded BigDataStack project[38], Worldline worked with a major retailer in Spain to build a recommender system based on open source that makes personalised product recommendations to consumers accessing their eCommerce website.

Similarly, a major German bank has built and tested a proof of concept for analysing their clients' personal and transaction data. They use ML to predict their client's financial futures as pensioners. Product recommendations are then made based on these insights. Subject matter experts have validated the reliability of the predictions and the idea has been tested with over 300 clients. The same bank is also seeking to reduce churn amongst their commercial clients by using AI to identify potential leavers and then automatically triggering actions via their CRM system.

Anomaly detection on data collected from ATMs can be used to predict failures

At Worldline, our fraud detection software uses the AI model score as one input to other rules. AI models are less predictable than manually configured rules (as they vary depending on the training data), but they can catch complicated interactions between many features that humans cannot imagine. This is why the two approaches are complementary. The current AI models within our fraud platform run within minutes and detect fraud on issuing card authorisations. In the future, we will include a real-time AI model (Gradient Boosting and Deep Learning based) for blocking transaction authorisations via the "WL Instant Score" module.

Preventative maintenance is another case where advisory AI can suggest actions in order to reduce downtime (and save costs). Worldline developed a proof of concept with a leading international consumer packaged goods company where data from coffee machines was analysed using different neural networks to predict failures of machines in bars and restaurants before they happened, thus allowing preventative maintenance to be performed and avoiding downtime and loss of revenue. We are also working on a similar use case where anomaly detection on data collected from ATMs can be used to predict failures.

Another use case is credit risk scoring. When coupled with explainable AI techniques, it can predict credit risk. It explains the basis of this prediction, whilst still leaving the final decision in the hands of a human assessor.

As you can see from these examples, the opportunity to use AI in an advisory capacity to support human decision making appears in many forms and avoids many of the challenges associated with fully autonomous AI.

Autonomous AI

Although often more challenging to implement (as explained earlier), autonomous AI can deliver significant benefits, allowing complex decisions to be made and actions to be taken at speed and at scale with no human involvement.

We consider the AI-based stand-in processing developed by Visa[39] to be one example of this. By using AI to make decisions that more closely mirror an issuer's own decision-making process, they expect to decrease transaction declines for cardholders by up to 50%.

At Worldline, we have been developing AI to augment Worldline's Online Payment Acceptance solution (WOPA) which routes transactions from merchants to acquirers. Currently the choice of which acquirer to route a transaction to is statically defined and solely based on the merchant. This limits the possible number of acquirers and does not take into account any change in the acceptance policy of the acquirer.

Worldline is implementing an AI-based solution where the system chooses the optimal path to an acquirer for each transaction dynamically. The solution selects the route based on the cost of processing the transaction and the refusal rate of the acquirer. To do this, the model uses reinforcement learning based on Contextual Bandit algorithms[40] to adapt iteratively and autonomously based on the feedback that it retrieves from each transaction that is processed. For us this is also an exciting demonstration of a real-world use case where an AI solution can learn the best way to solve a problem without any prior training.

38 https://bigdatastack.eu/project

39 https://usa.visa.com/about-visa/newsroom/press-releases.releaseId.17301.html

40 https://www.microsoft.com/en-us/research/blog/new-perspectives-on-contextual-bandit/

Creating a hyperautomation culture

Organisational change

So far, we have discussed how AI can be applied to automation, both as a perception layer and for decision making, and we have explored the importance of data-awareness. However, organisations can only successfully implement these technical building blocks if they also create a hyperautomation culture. As such, strong leadership and effective organisational change management are crucial.

Strong leadership and effective organisational change management **are crucial**

In this section we will not describe everything required for successful organisational change management, but we will draw out some specific aspects that we believe are especially relevant to hyperautomation.

Fear of job losses

The Boston Consulting Group developed a model for the behaviour of people (or groups of people) within an organisation. It was based on the idea that people's behaviour can be understood by being aware of their goals, resources and constraints[41].

From this, we conclude that if people are not supportive of hyperautomation, there is a high likelihood that they are behaving rationally and that they believe that resisting or blocking the change is the best way for them to achieve their goals (using their resources and within their constraints). What Boston Consulting Group suggests is that, if you wish to see a change in this behaviour, you should seek to change their goals, resources and/or constraints.

Implementing hyperautomation will usually involve reviewing and changing existing processes, work behaviours, organisational structure and technologies: potentially radically reshaping the work environment.

While such changes may be positive for the company (e.g. improving competitiveness), employees may fear that their roles will change (in ways they may not like) or that they will lose their jobs altogether. Given these fears, it is entirely rational for them to resist and block the transformation.

Decades ago, successful Lean transformations in manufacturing were achieved by companies committing to their staff that "no one would ever lose their job due to the introduction of Lean thinking...although the nature of everyone's job would constantly change"[42]. For successful hyperautomation, a similar pledge is required, backed by education and reskilling programmes to help those who are impacted make the transition into new roles. If a headcount reduction is required, it should take place before a hyperautomation initiative starts.

41 A Framework for Analysing Organisational Behaviour published by Boston Consulting Group in their discussion paper "Strategic Workforce Engagement: Designing the Behavior of Organizations for Competitive Advantage", accessed from: https://www.bcg.com/documents/file14006.pdf

42 Lean Thinking: Banish waste and create wealth in our corporation, 1996, James P. Womack and Daniel T. Jones

How to manage AI

A similarly rational fear may come from those in managerial positions. If the work of their teams is automated, what will happen to them? Will they still be required? Whilst they may have years of experience of managing people, how can they apply this to managing AI algorithms? In some cases, managers may simply lack the knowledge of AI and its benefits; in other cases, they may fear losing control and power.

The virtuous cycle of AI

Another paradigm shift that needs to be embraced is the Virtuous Cycle of AI-based Product Improvement, as shown in Figure 8[43]. Where traditional product management is based on a linear process of understanding customer needs and then developing features to meet them, AI-based products follow a virtuous cycle where a great product attracts more users, those users generate more data, and that data helps to improve the product.

On this basis, an AI solution cannot be managed in a traditional way. Rather, an evolutionary approach is needed, with continuous changes brought about by the data that is generated.

Such an approach requires dedicated experts to identify the substantive content of the data, including the most accurate extraction of information to achieve desired outcomes. However, this is not enough; operational teams augmented with AI expertise must also be involved to manage the specific needs of an AI product in terms of process knowledge, resource performance, access guarantees and continuous AI-specific updates. Organisations must also adopt these operational techniques by integrating the additional costs generated by continuous monitoring of the changes required by an AI product's long-term management.

At XOKind we are using the virtuous cycle of AI-based product improvement described in this white paper to create delightful, AI-powered personalized customer experiences. These are underpinned by another topic covered in this paper: the revolution in natural language understanding driven by the advent of large neural network models.

Arjun Bansal
CEO & Co-founder, XOKind.
Previously co-founder Nervana Systems (acquired by Intel) & VP of AI Software and Research at Intel

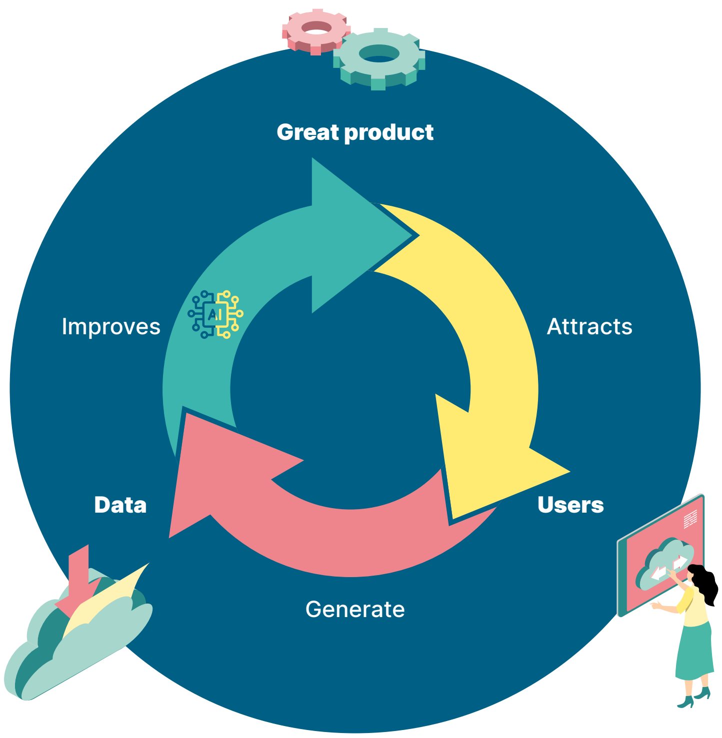


Figure 8: The Virtuous Cycle of AI-based Product Improvement

43 Diagram inspired by Machine Learning course (CS229) at Stanford University by Andrew Ng, accessed from: http://cs229.stanford.edu/materials/CS229-DeepLearning.pdf

Conclusion

In this paper we have explained how AI is driving a trend from automation towards hyperautomation: with computers now able to perform tasks, make decisions and take actions that were once the sole preserve of humans. Many businesses are already achieving significant cost optimisation with hyperautomation expected to save 20-30% of manual effort in the coming years. However, savvy businesses are not only looking to optimise what they do today: they are using hyperautomation to enable new business models and deliver highly personalised customer interactions.

The journey to hyperautomation is not an easy one. Becoming an organisation with the right mix of skills, technical infrastructure and data maturity to spot great use cases for AI and then implement them rapidly is not easy. In Figure 9 we present the main topics covered in this paper as a roadmap to help you with this journey.

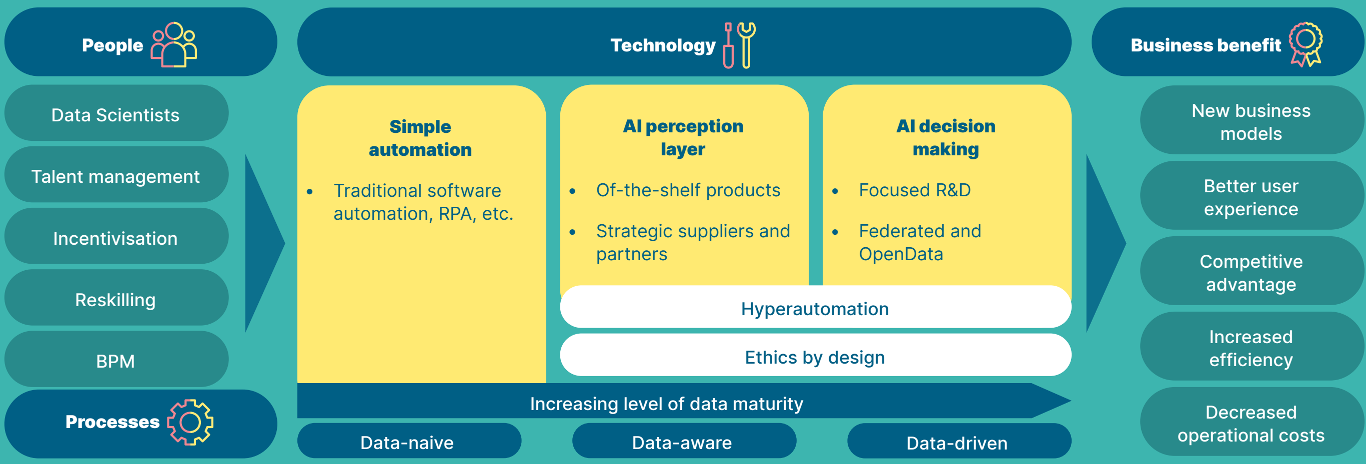


Figure 9: The journey towards hyperautomation

Understand your starting point

We recommend you begin by understanding where you are today in two dimensions:

The first dimension is your current AI maturity. Use an AI maturity assessment[44] to understand your current capability in terms of people, technology and data maturity.

The second dimension is your current business processes. Use Business Process Mapping (BPM) to gain insights into how your processes operate today and understand which steps could benefit from hyperautomation. Those which currently require a large amount of human effort but are also somewhat repetitive and error-prone will typically be top candidates.

Close skills gaps

From your AI maturity assessment, identify how you can fill any skills gaps that you have to meet your business objectives (short-term, mid-term and long-term). As we have seen, AI is a useful tool for specific kinds of use cases. To identify these use cases, many people within the organisation, including product managers, sales leads, solution managers, business domain experts, and technical architects must know enough about AI to spot those opportunities. Furthermore, they must have rapid access to people with more in-depth expertise, to quickly qualify which use cases should progress further. You should also seek to incentivise the application of AI. Ways to do this include mechanisms such as a dedicated centralised proof of concept budget to support proposals for using AI to solve a business use case, or allocating 20% of their time for people to advance their knowledge of AI and conduct related research. Use the money saved through the automation of simple tasks to invest in the automation of more complex tasks, including training and reskilling those whose work has been automated.

Boost your data maturity

Most organisations will be somewhere on the spectrum from data-naive to data-driven. Determine which combination of top-down and bottom-up initiatives you need to put in place to increase your level of data maturity. Strive to make data that you have within your organisation accessible in a trusted and secure way and build the capability to ingest and understand data to gain insights from it. Consider how you might participate in initiatives and platforms that enable data sharing between organisations.

Make-or-buy

Not all organisations will have the required skills and data maturity needed to build their own AI solutions, whether by customising off-the-shelf components or by crafting and training their own algorithms. In these cases, it makes sense to rely on external providers, challenging them to demonstrate their current AI credentials and explain how they plan to leverage AI further in their product roadmaps.

Even if you have the capacity to do much yourself, generally it will still make sense to focus your in-house efforts on your core business. In these cases, we recommend that you use 3rd party components to provide the perception layer. Progressing to using AI for decision making, either in an advisory capacity or autonomously, will often demand a deeper understanding of AI models, and may also require access to data to train them. For this, you will require data analysts, data scientists and data engineers who can work in collaboration with business domain experts, software architects, software engineers and operations personnel to efficiently develop solutions based around AI..

---

44 Such as the one published by Ovum: https://www.amdocs.com/sites/default/files/filefield_paths/ai-maturity-model-whitepaper.pdf

Explainability and ethics

Retrofitting solutions to meet the challenges of accountability, acceptability, explainability and measurability can be difficult or impossible. Apply the Ethics by Design approach and align with guidelines such as the European Union's "Ethics Guidelines for Trustworthy AI".

Start now

As we highlighted at the beginning of this paper, organisations that do not embrace hyperautomation face being outcompeted by those that do: not only will they be less efficient, but they risk failing to engage customers and being unable to take advantage of new business models.

> Organisations which do not embrace hyperautomation face **being outcompeted** by those that do

It should also be clear that the journey to hyperautomation is not an easy one. There are many ingredients required for success, all of which are interdependent. The exact recipe will be unique for every company, depending on the nature of their business and what their starting point is today. In this paper we have shared the many insights we have gained from our journey, and we hope that these, combined with our recommendations, will help you progress on your own journey towards hyperautomation.

Key takeaways

Understand your current processes and AI maturity

Analyse your current business processes and assess your AI maturity to identify what you can automate and how.

Close skills gaps

Educate and incentivise people to spot good use cases for hyperautomation and to have the skills to implement these solutions efficiently.

Increase the data maturity of your organisation

Identify which top-down and bottom-up initiatives you need to launch so that data across your organisation can be accessed and understood in a secure and trusted way.

Take make-or-buy decisions

Challenge external providers to demonstrate their AI credentials and focus your in-house efforts on applying AI to your core business.

Determine where to focus your AI research efforts

Target your research efforts on AI for decision making where you will require a deeper understanding of AI models and access to the data to train them.

Ensure AI explainability and Ethics by Design in your AI systems

Ensure that explainability and ethical considerations are taken into account from the outset in AI initiatives.

Authors

This paper was prepared by the Worldline Scientific Community and authored by the following people from across the organisation:

- Gert-Jan Andries, *Head of Retail Transformation, Belgium*
- Julien Carme, *PhD, Data Scientist, France*
- David Daly, *Global Deal and Delivery Assurance Manager, UK*
- Magnus Danielsson, *UK CTO, UK*
- Urs Gubser, *Head of Merchant Transformation, Switzerland*
- Dalila Hattab, *PhD, Head of Financial Services Lab, France*
- Liyun He-Guelton, *PhD, Head of Worldline Labs Machine Learning Skill Centre, France*
- Adrian Hepworth, *UK Chief Architect, UK*
- Adrian James, *Technical Director, UK*
- Yacine Kessaci, *PhD, Worldline Labs Senior AI Researcher, France*
- Nicolas Kozakiewicz, *MBA, Innovation Executive Advisor, France*
- Minh Le, PhD, *Head of Connected Vehicle & Emerging IoT Offerings, Netherlands*
- Jose Maria López, *Head of Bus. Dev. Mobile Competence Centre & Innovation, Spain*
- Frederic Oble, PhD, *Worldline Labs Head of Scientific & Technical Direction, France*
- Rob Price, *UK*
- Maissaa Rharrab, *Global Transformation Programme Manager, Belgium*
- Robert Rohrkemper, *PhD, Senior Data Scientist, Switzerland*
- Laurent Rousee, *MBA, Group Offshore Demand Manager, France*
- Jonathan Sauer, *Financial Services Innovation Manager for Benelux, Belgium*
- Wissam Siblini, *PhD, Machine Learning Researcher, France*
- Myles Simpson, *Fraud Business Development & Strategy, Belgium*

We are also grateful to Arjun Bansal, Stephan Blachier, Martin Brown, Lisa Coleman, Marc-Henri Desportes, Matthias Fengler, Gilles Grapinet, Antoine Guillaume, Andy Jin, Wolf Kunisch, Rafael Lalive, Tayeb Laouar, Johan Maes, Anthony Marrevee, Esperanza Moreno and Ueli Rutishauser who all provided valuable insights and feedback during this paper's preparation.

About Worldline

Worldline [Euronext: WLN] is the European leader in the payments and transactional services industry and #4 player worldwide. With its global reach and its commitment to innovation, Worldline is the technology partner of choice for merchants, banks and third-party acquirers as well as public transport operators, government agencies and industrial companies in all sectors. Powered by over 20,000 employees in more than 50 countries, Worldline provides its clients with sustainable, trusted and secure solutions across the payment value chain, fostering their business growth wherever they are. Services offered by Worldline in the areas of Merchant Services; Terminals, Solutions & Services; Financial Services and Mobility & e-Transactional Services include domestic and cross-border commercial acquiring, both in-store and online, highly-secure payment transaction processing, a broad portfolio of payment terminals as well as e-ticketing and digital services in the industrial environment. In 2020 Worldline generated a proforma revenue of 4.8 billion euros.

worldline.com

For further information
WL-marketing@worldline.com