

# AI and Machine Learning for Complex Business Decision Making



## PART 1—FROM EXCEL TO AI: THE ANALYTICS EVOLUTION

In **Part 1** of this six-part series of 10-minute reads, we present highlights of the [2020 MMPA Conference](#),<sup>1</sup> **AI and Machine Learning for Complex Business Decision Making**, to illustrate the versatility and ubiquity of new digital technologies and to spotlight CPAs' changing competencies and emerging opportunities.

Here, [Part 1-From Excel to AI: The Analytics Evolution](#) looks at the **analytics evolution** and the way CPAs in finance and audit need to adapt their analytics skillset to keep up with this rapidly changing field.

[Part 2 - Technology for Problem Solving](#) warns against the **digital transformation trap**: losing sight of problem solving and, instead, following the lure of technology. How should CPAs assess AI technology and value creation?

[Part 3 - Systems Thinking and a Framework for Applying AI](#) looks at **systems thinking** – a critical-thinking competency for CPAs – and a **framework** for applying AI and machine learning to complex business decision making.

[Part 4 - Data and Trust](#) examines **data management value chains**, new roles for CPAs and initiatives to ensure that data and AI systems are used fairly, accountably and transparently.

1 The 2020 MMPA Conference was hosted by the Master of Management & Professional Accounting (MMPA) Program and BIGDataAIHUB at the Institute for Management & Innovation (IMI), University of Toronto at Mississauga (UTM). The MMPA Program combines an MBA curriculum with the development of technical and leadership skills vital for the accounting profession.

[Part 5 - Humans, Machines and Humachines](#) focuses on **human skills**. It introduces AI-augmented intelligence in emerging organizations called **humachines** and the way CPAs' human and technical skills can play a role in commercializing Canada's AI start-ups.

[Part 6 - Moving to an AI Advantage](#) looks at the way companies move to an **AI advantage** and steps CPAs can take to be future ready.

## Introduction

In a six-part series of 10-minute reads, **AI and Machine Learning for Complex Decision Making** presents highlights from the [2020 MMPA Conference](#)<sup>2</sup> hosted by the [Master of Management & Professional Accounting \(MMPA\) Program](#) and [BIGDataAIHUB](#) at the [Institute for Management & Innovation \(IMI\), U of T Mississauga \(UTM\)](#). The series illustrates the versatility and ubiquity of new digital technologies and spotlights CPAs' changing competencies and emerging opportunities.

### COMPLEX VS. COMPLICATED PROBLEMS

“**Complicated** problems differ from **complex** ones” (CPA Canada Foresight, et al., 2021, p. 4). “They are often technical in nature and have linear solutions, the type humans are good at” (Benjamin & Komlos, 2019).

“Although complicated problems are challenging to solve, once solutions are found, they generally stay solved” (CPA Canada Foresight, et al., 2021, p. 4).

“Complex problems, on the other hand, are not solvable by applying static algorithms, rules and processes” (CPA Canada Foresight, et al., 2021, p. 4). “These problems are what machines are good at: multi-dimensional problems that cannot be solved with linear thinking...For example, fixing a car is complicated; disrupting the automotive industry is complex” (Benjamin & Komlos, 2019); “implementing a new policy is complicated; transforming a company's culture is complex” (Speaker Michael Lionais).

“Complicated thinking is the default managerial approach, but treating a complex problem as though it were complicated leads to costly mistakes and potentially disastrous unintended consequences” (CPA Canada Foresight, et al., 2021, p. 4).

This six-part document is one of a series of collaborative publications by CPA Canada to explore AI and its impact on the CPA profession. We are pleased to present this publication on the [2020 MMPA Conference, AI and Machine Learning for Complex Business Decision Making](#), in collaboration with an important academic stakeholder, the [Master of Management & Professional Accounting \(MMPA\) Program](#) at the [Institute for Management & Innovation \(IMI\), University of Toronto at Mississauga \(UTM\)](#).

We present highlights of presentations by six leading academics, practitioners and innovators and share their expertise and advice.

This six-part series' aim is to help current and prospective CPAs understand AI and the way they can play a role in the rapidly changing business environment, particularly in their organization's path to **value creation**. The **value creation** concept is important but can be interpreted in many ways. It is explored in detail in CPA Canada's [Value Creation Decisions and Measurement Primer](#).

2 The MMPA Program hosts a one-day MMPA Annual Conference on topics that are particularly important and timely for business and/or the accounting profession.

The CPA profession needs to shift focus from hindsight to foresight by embracing new methods and technologies which allow them to harness the power of information in this data-driven world. I encourage CPAs to [join the conversation](#) on transforming the future of our profession.

DAVINDER VALERI, CPA, CA, CPA CANADA

Although speakers caution the audience that AI is not the only way to solve business problems, the data explosion means that computing power is necessary for humans to deal with data and problems that are increasingly complex. Speakers present applications of AI and machine learning to improve complex business decision making, whose implicit goal is some sort of value creation. In these talks, that value creation takes the form of innovation, improvements to workflow, or product or service delivery. Sometimes, however, those applications do not lead to **value realization**, and the speakers explain how to avoid that pitfall.

That implicit goal of value creation is important for accountants (CPAs), says speaker [Michael Lionais](#), because “...to remain relevant they have to move from being keepers of the finances to becoming proactive contributors to the real-time evaluation of a broader understanding of performance.”<sup>3</sup>

The game is changing. When used appropriately, AI can help decision makers reduce the traditional trade-off between quality and quantity of information.

MICHAEL WONG, CPA, CA,  
CPA CANADA

### A WORD ABOUT TERMINOLOGY

Despite the conference’s moniker, the speakers seldom use the terms “AI” and “machine learning.” Instead, they talk about “machines,” “analytics” and “applying technology.”

AI is a broad term. Artificial intelligence is the science of teaching programs and machines to complete tasks that normally require human intelligence. Machine learning is a technique within the AI sphere. It uses algorithms that “learn” from experience (i.e., it uses and learns from data sets). The algorithms create computational models that process large data sets to predict outputs and make inferences (CPA Canada & AICPA, 2019, p. 10).

3 Speaker Michael Lionais, from *CPA Canada Foresight: The Way Forward* (Toronto: 2019), p. 9.

As we move forward, collaboration becomes more important – including collaboration between CPAs and other experts (such as data scientists) but also collaboration between educators and the profession.

IRENE WIECEK, FCPA, FCA, UNIVERSITY OF TORONTO

## PART 1–From Excel to AI: The Analytics Evolution

In this section, **Thomas Davenport** looks at a half century of change from human-driven to technology-driven analytics for problem solving in the **analytics evolution**. **Pavel Abdur-Rahman** provides an overview of **technology in banking services** applied to clear examples of paths to value.

Analytics aren't new to CPAs. Particularly in financial reporting roles, CPAs use "...historical data and assumptions to model and forecast financial results" (CPA Canada, 2019, p. 9). But data and analytics are changing.

Speaker **Michael Lionais** says that CPAs do not need to become computer scientists but do need to understand data analytics, big data and the logic of programming. Accountants have always been data processors, so they need to adapt that skillset. **Thomas Davenport** says that "Accounting not only has to catch up with analytics but also needs to keep up with this rapidly changing field ..." (Tschakert et al., 2016).

### From Excel to AI: The Analytics Evolution

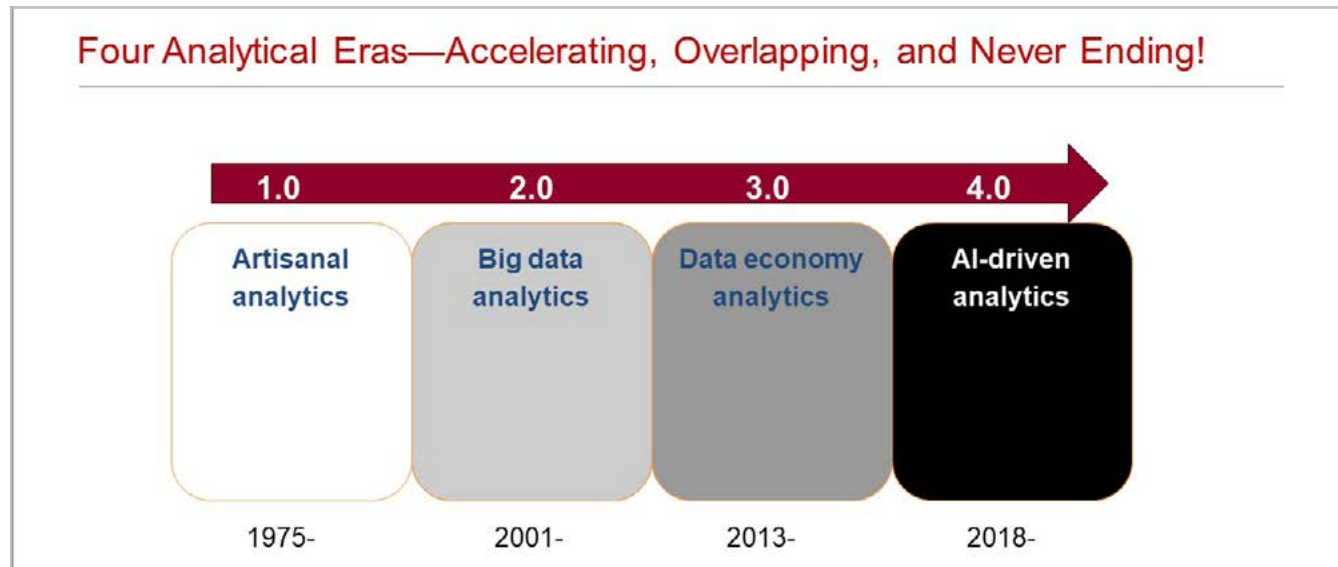
Since about 1975, four eras of data analytics have supported business decision making, Davenport says (see **Figure 1.1**). The division between them is fuzzy, because none has an end-point and none goes away. The "eras" are just a convenient construct for visualizing the analytics evolution: the transition from Excel models and structured databases to increasingly sophisticated AI-technology-driven machine learning with unstructured/big data.

#### DATA AN·A·LYT·ICS

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The use of math and statistics to derive meaning from data to make better business decisions (Harvard Business Review, 2018). These tools do not necessarily need AI, but increased computing power is needed to keep up with the explosion in amounts and types of data.

FIGURE 1.1: FOUR ANALYTICS ERAS [SOURCE: SPEAKER THOMAS DAVENPORT]



**Analytics 1.0 – Artisanal analytics** are “by hand”: They have a big human component, because they are labour and time intensive. **Business intelligence analysts** focused on helping managers inside the organization make better decisions. Prediction was based on human hypotheses, and that meant looking for correlations between variables in **small data**. Small data is relatively structured and not that large (e.g., a company’s data on its customers).

*For Analytics 1.0, think limited, pre-AI computing power used on desktop computers: **Excel** used by finance departments for budgeting, analyzing and forecasting sales, based on historical data; early versions of statistical software used to analyze business operations (e.g., [SAS](#)) or to help market researchers understand customers (e.g., [SPSS](#)).*

#### A NOTE FOR CPAs

“**These [older] tools** usually continue to work, and there is a natural – but dangerous – human tendency to leave well enough alone.”

“...**[N]ew tools** have led to a dramatic increase in the speed and scale with which analytics can be performed, and much greater integration with business processes.”

“...Most organizations don’t regularly evaluate the ‘cost of preserving the status quo,’ but it can be rather substantial in the case of analytical technologies.”

DAVENPORT, 2017a

**Analytics 2.0 – Big data analytics** became popular in Silicon Valley companies. “This was a period of adapting to different types of data. Unstructured data included video and text data, etc., that is structured differently than rows and columns of numbers,” says Davenport. Large, complex data sets containing structured and unstructured data – **big data** – could not be managed with traditional data processing.<sup>4</sup> Needed statistical and analytical capabilities were created by new quantitative analysts called **data scientists**. Open-source software emerged, which allowed fast batch processing of big data over parallel servers (Davenport, 2013), and programming languages Pig, Hive and Python were used for structuring big data and making it ready for statistical analysis (Davenport, 2017b). Data scientists moved analytics away from internal-decision support to online tools directed at customers, and they could sell data collected from those users. This industry became one of the earliest to adopt AI and machine learning.

*For Analytics 2.0, think Google, Facebook, eBay, LinkedIn and [Airbnb](#).*

Accounting has had a very transactional orientation, using descriptive analytics on structured, small data. Predicting financial performance with performance measures, including nonfinancial measures, “...presents a great opportunity for accountants to provide a much more valuable role to management. Accounting not only has to catch up with analytics, but also needs to keep up with this rapidly changing field.”

THOMAS DAVENPORT (TSCHAKERT, ET AL., 2016)

**Analytics 3.0 – Data economy analytics** moved big data out of Silicon Valley to general use. Analytics 2.0 start-up companies (above) grow to embrace Analytics 3.0. Data- and analytics-based products appear in every business; AI and machine learning become more widely adopted. Traditional small-data analytics blend seamlessly with big data (e.g., companies like Best Buy blend customer data with geographical data to recommend products to in-store customers or with what customers say on social media for highly targeted marketing). Business decision support takes on an industrial, not artisanal scale, because it is based on enormous amounts of data. Some companies now compete on their analytical capabilities and so adopt more AI and machine learning.

*For Analytics 3.0, think real-time product recommendations (Amazon, Google, Netflix, Airbnb) or real-time routing of delivery vehicles for speedier, safer, more fuel-efficient trips – with no left turns (e.g., UPS’ [ORION](#)).*

4 For more information, see CPA Canada. (2019). *A CPA’s Introduction to AI: From Algorithms to Deep Learning*. CPA Canada.

**DATA AN·A·LYT·ICS**, *continued*

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There are four main types of analytics (CPA Canada & AICPA, 2019, pp. 15-16):

1. **Descriptive analytics** help organizations understand *past* events – like annual performance. Charts, graphs and dashboard are types of **data visualization** used to gather insights.
2. **Diagnostic analytics** go a step further. They examine data to answer *why* past outcomes happened. Techniques include drill-down, data mining and correlations (e.g., increased online widget demand was driven by Millennials with children in condos in eastern Canadian cities).
3. **Predictive analytics** predict outcomes that will *probably* happen. Past data can be used to train machine learning models for, say, supply chain management to forecast demand for a company’s widgets.
4. **Prescriptive analytics** go even further by *recommending actions* to arrive at those predicted outcomes (e.g., by generating ways to optimize production or inventory volume). In a supply chain, for example, prescriptive analytics may assess the inputs needed and launch a production run for any missing materials to complete the manufacturing of widgets on order.

**Analytics 4.0 – AI-based analytics** in many cases by-pass humans. Analytics 1.0, 2.0, 3.0 prepared analytical results for “...human decision makers who considered the output and made the final decision” (Davenport, 2017b). But now, with increased data and results being too labour intensive or complex for humans, “...machine learning technologies can take the next step and actually make the decision or adopt the recommended action. Most cognitive technologies are statistics-based at their core, and they can dramatically improve the productivity and effectiveness of data analysis” (Davenport, 2017b).

*For Analytics 4.0, think some human job replacement, but expect augmentation rather than large-scale automation: humans and machines working closely with each other as colleagues. (Explored further in [Part 5 – Humans, Machines and Humachines](#).) For example, Toronto-based [Kira Systems](#) helps lawyers and auditors make meaning from unstructured contracts and documents. Using machine-learning contract analysis, it can identify content relevant to audit questions. For Analytics 4.0, think also banking services. ([See Use Case: Analytics 4.0 in Banking Services.](#))*

For audits, AI algorithms can quickly analyze vast amounts of data on which CPAs can provide deeper insights than those based on small sample sets (CPA Ontario [2019], p. 18).

“A significant number of companies in Canada expect their external auditors...to use audit data analytics (ADAs), regardless of the size of the audit firm” (CPA Canada, 2017, p. 1).

CPAs may need to start auditing algorithms and data sets as more companies adopt AI (CPA Ontario [2019], p. 17)

## Use case: Technology in banking services

### USE CASE: Technology in Banking Services [Analytics 4.0]

(Pavel Abdur-Rahman)

Disruption from FinTechs, and tech giants, increasing security risk and fraud risk are among the forces driving technology innovation and transformation in the banking industry. IBM's [Pavel Abdur-Rahman](#) introduces paths to value with examples specific to **banking services**.

Creating value in banking services is all about Analytics 4.0.

Each of the 12 use cases for improving customer engagement and managing risk ([Figure 2.1](#)) names the value creation goal and describes the path to that value. All of these use cases rely on AI-driven analytics in the background. They clearly describe a business solution expected to generate value and the role that users or analytics would play in the solution.

FIGURE 2.1: PATH-TO-VALUE USE CASES FOR FINANCIAL SERVICES

Improve Customer Engagement		Better Risk Management
<p><b>1 Cross sell / up-sell</b> Predict the additional products customers are most interested based on customer profile and behaviours and make recommendations</p>	<p><b>5 Next-best-action</b> The ability to understand what would be the next best interaction that the bank can have with the customer</p>	<p><b>9 Credit Decisioning</b> Predict defaults more accurately, identify the customers who are at risk, proactive warnings and effective collections strategy</p>
<p><b>2 Personalized Marketing</b> Better predict the customer's preferences and target the right customers with marketing campaigns of products</p>	<p><b>6 Customer Sentiment Tracking</b> Monitor and understand what the customer is really saying and/or feeling about the credit union, and take proactive actions</p>	<p><b>10 Anti-Money Laundering</b> Analyze AML triggers against client transactions and use advanced analytics to flag suspicious activities</p>
<p><b>3 Loan and Deposit Pricing</b> Smart / dynamic pricing strategy based on customer profile, product portfolio, transaction / behaviour history, etc.</p>	<p><b>7 Dynamic / micro-segmentation</b> Customer segments should include enhanced insight into customer profiles, buying behaviours and patterns, prior marketing responses, social media activities</p>	<p><b>11 Fraud Detection</b> Use advanced analytics to identify abnormal spend patterns and detect suspicious transactions</p>
<p><b>4 Lifetime Value Prediction</b> Long term sustainability of earnings and profits is dependent on identifying the customers that have a higher value currently and have a positive potential in the future</p>	<p><b>8 Customer Attrition Reduction</b> Forecast the probability of a Customer to churn and when and take proactive actions to retain the customer</p>	<p><b>12 Cyber Security</b> Use machine learning and AI to detect potential cyber threats and improve cyber security</p>

Source: Pavel Abdur-Rahman and IBM.

Note: The title of each use case (#1-12) is the value creation goal, with the path to that value described below.

But consider this. Abdur-Rahman says that implementing these use cases requires customers to **trust** the background AI (from data collection all along the path to value) and to **trust** the enterprise with the use of their data. How the financial services sector – including banking services – will achieve trusted data and trusted AI is covered in [Part 4's section on Gaining Trust in Data and AI Systems](#).



### To join the game, use a systems approach

AI adopters – large and small – can buy or rent capabilities rather than build them in-house, says Davenport, because automated, customizable machine-learning systems are available from many vendors. This means that even small companies can join the competition. Cloud vendor [DataRobot](#), for example, says on its website that it is “...the leading end-to-end enterprise AI platform that automates and accelerates every step of [the] path from data to value” by “delivering trusted AI technology and ROI enablement services to global enterprises and individual users.”<sup>5</sup> IBM Research has developed an open-source [AI Explainability 360 Toolkit](#) to help financial services organizations make decision making clear to consumers.<sup>6</sup>

[Nada Sanders](#) warns that “Machines are just tools. They cannot fix bad processes, poor management practices, or failing employee morale. The idea that implementing technology, acquiring software, or purchasing better data will simply follow a ‘plug-and-play’ approach is misguided. This is the old paradigm of technology. We need to break it” (Sanders & Wood, 2020, p. 192). Adopting technology means applying it to solve a problem or to improve a business process ([Part 2](#)) and taking a **systems approach** to your organization ([Part 3](#)).

[Part 2](#), the next part in this six-part series, warns against the **digital transformation trap**: losing sight of problem solving and, instead, following the lure of technology. How should CPAs assess AI technology and **value creation**?

5 DataRobot [Website] (2021). [Example from speaker Thomas Davenport.]

6 Speaker Pavel Abdur-Rahman shares a video on IBM Research’s *AI Explainability 360 Toolkit*.

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