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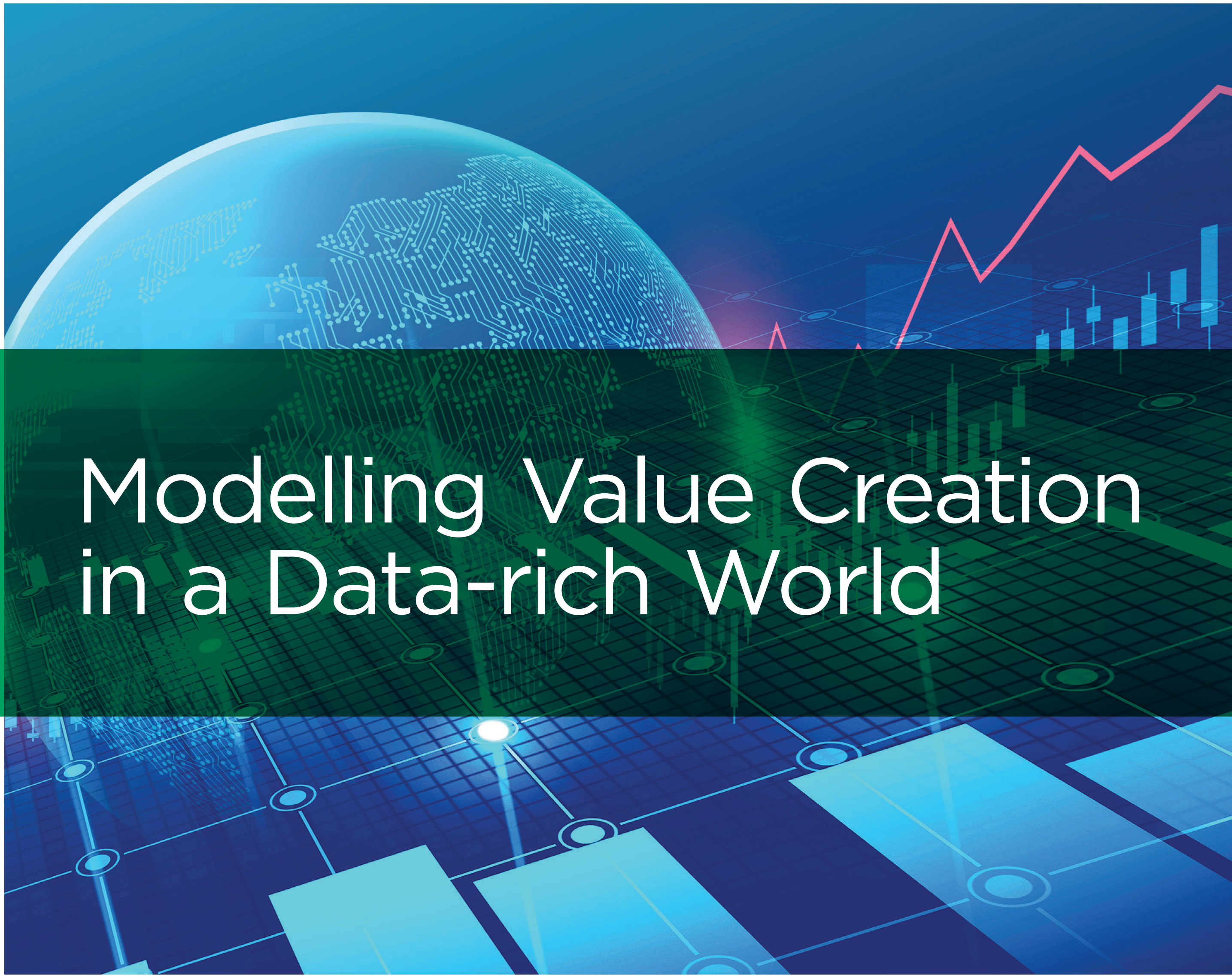

Modelling Value Creation in a Data-rich World

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Table of Contents

Introduction

In 2018, CPA Canada launched a Foresight process designed to chart the path forward for the CPA profession. The conclusions of the initial exploratory phase of this process were documented in *The Way Forward*. The Foresight vision calls for a transformed profession that moves beyond its traditional focus on financial transactions to place a new emphasis on value creation measured by broader financial and non-financial metrics, from the perspective of multiple stakeholders.

> Our traditional mindset of looking back in time to report on what has already occurred must be reoriented to a real-time and forward-looking point of view. New and emerging technologies will combine with the digitization of corporate information and allow real-time automated reporting. This will support much more sophisticated modelling of what will occur in the future.
>
> [See *The Way Forward*, 9. Also, see Appendix A for a summary of CPA Canada initiatives aimed at transforming the CPA profession in the directions recommended by *The Way Forward*.]

As CPAs work to prepare their organizations for the future anticipated by *The Way Forward,* they face a fundamental challenge. Measuring forward-looking value creation requires a mindset, approach and technical skills that are very different from the ones required by measuring historical financial transactions summarized in traditional financial statements. Transactions by their very nature have already happened in the past.

However, value creation involves looking forward. In *Leading the Way: Competency Map 2.0*, value creation is defined as follows:

> [The] process by which an organization generates, preserves or allows to erode future financial and non-financial value streams and outcomes for the organization and its stakeholders in an ethical and sustainable manner.
>
> [See *Leading the Way: Competency Map 2.0*, 29].

How can CPAs measure or quantify forward-looking value streams? Because they happen in the future, quantifying value streams requires use of appropriate modelling techniques. Why attempt to quantify future value streams? We do so in order to gain insights that help businesses and stakeholders optimize those value streams as they are realized in future. Optimizing value streams involves making a series of informed business decisions.

This paper presents a framework developed to help CPAs design optimal modelling approaches, given the nature of the business decisions they need to support.

1. Business modelling fundamentals

1.1 What is a model?

In its most basic definition, a model is a simplified representation of reality.

Models have widespread application in many fields of endeavour, including various scientific disciplines, weather forecasting, mathematics, economics, social sciences, health care, education and business. This paper focuses on models used to support a business decision.

A model enables the business to consider one or several scenarios in its decision-making process. It can also facilitate risk assessment, challenging assumptions and understanding the impacts of a decision before taking it.

In general, all models include data inputs, inferences arising from analysis of the data, assumptions, processing based on the inputs, analysis and assumptions, and outcomes generated by a model.

1.2 When should a business use a model?

A business should use a model to support a decision whenever the benefits of using a model to inform decisions significantly exceed the cost of developing the model. Models should help business leaders gain clarity on decisions that have inherent uncertainty. By developing a robust set of assumptions and applying those assumptions to a mathematical representation of a business-operating structure, future investments or corporate actions can be "simulated," thereby affording the ability to visualize the impact that such decisions can have on the business. Simulating business operations to support decision-making is sometimes referred to as "digital twinning."

1.3 How does using a model enhance business decisions?

Models help enhance business decisions by generating data-driven insights into the factors that influence potential outcomes of those decisions.

In a business context, the first consideration is defining the specific decision(s) that a model is intended to inform. For instance, the specific decision could range from a recurring decision (such as how much credit to allow trade customers) to a one-time strategic decision (such as making a significant investment to enter a new market).

Having identified the decision(s), the next consideration is defining what data is required to develop data-driven insights to enhance the likelihood of achieving a better business decision (i.e., faster or more informed). Whether appropriate data is available depends on the level of sophistication of the organization's approach to data, and more specifically on the existence of a data strategy. (For additional detail, see 2.8 below for a summary of the CPAs role in data.)

Assuming that a data strategy exists and appropriate data is available, consideration can be given to the way a model is intended to inform the decision(s). The outcomes generated by a model could define a range of possibilities (such as best-case and worst-case scenarios), explore the range of uncertainty associated with outcomes (such as estimated probabilities associated with specific outcomes) and provide insight into the drivers of uncertainty that should be mitigated to increase the likelihood of achieving a desired outcome.

1.4 What categories of data analytics can be built into a business decision support model?

Business models are typically designed to apply one or more of the following categories of analytics to the data:

- descriptive – analysis that provides insights into past outcomes
- diagnostic – analysis that provides insights into why past outcomes occurred
- predictive – analysis that provides insights into future possible outcomes
- prescriptive – analysis that provides insights into factors that influence possible future outcomes and into actions that could be taken to maximize the odds of desired future outcomes

1.5 Does a business decision support model predict the future?

No. There is an important distinction between a “prediction” and “predictive analysis.” A prediction asserts that a specific outcome will occur. Predictive analysis identifies a range of possible future outcomes and may suggest a set of factors that are more or less likely to influence the probability of alternative outcomes. Prescriptive analysis can also identify the key drivers of uncertainty that should be mitigated to increase the likelihood of achieving a desired outcome.

In general, the factors that influence future reality are infinitely more complex than any model can possibly be or for which relevant and measurable data can be reasonably secured. While machine learning and artificial intelligence are increasing the sophistication and the reliability of models historically limited by significant uncertainty in input factors or assumptions, there is still uncertainty arising from the fact that the future does not necessarily resemble the past as captured in the datasets available for analysis.

1.6 Does a business decision support model provide a forecast similar to a weather forecast?

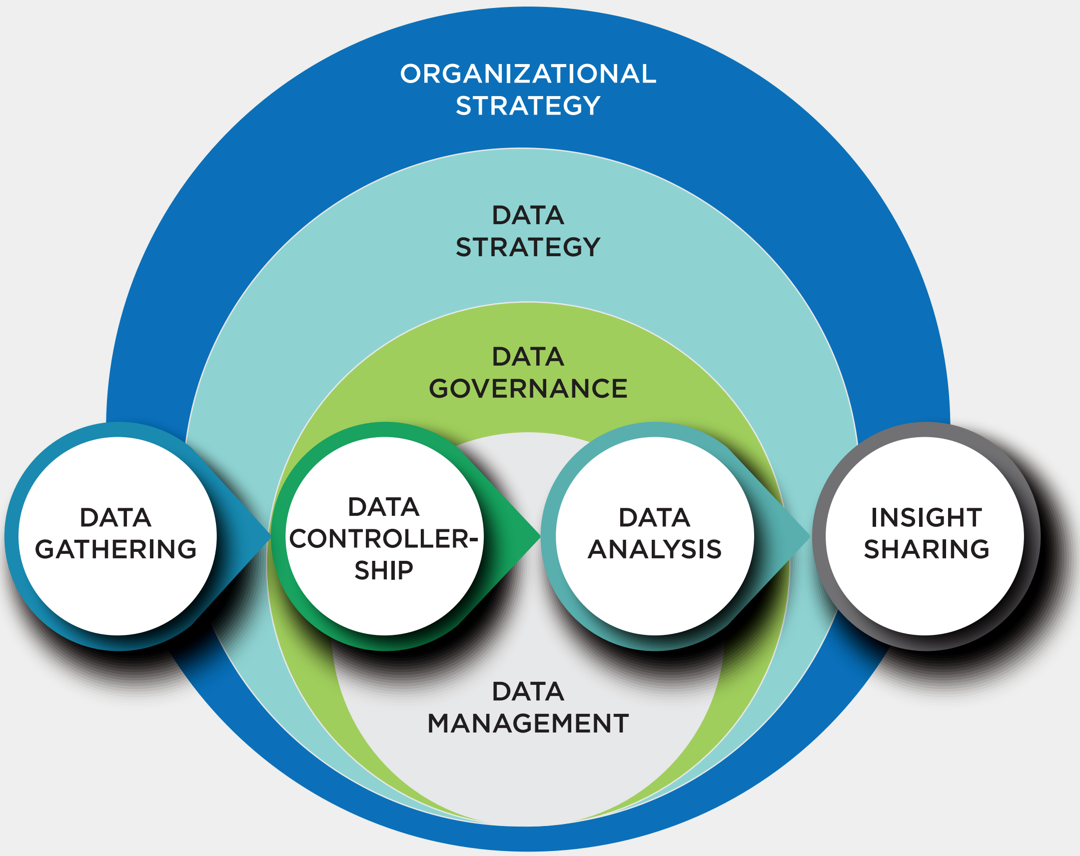
Only superficially. Modern weather forecasts are based on highly complex computer programs that take millions of inputs from around the world to produce a model of winds, temperatures and other weather variables for a short time into the future. The validity of weather forecasts is limited in time – a few days or weeks at the most. By contrast, most business decision support models deal with outcomes many months or years into the future, and use more limited datasets.

1.7 How does an organization ensure appropriate data to fuel a business decision support model?

CPAs have an important role in ensuring that an organization has access to optimal datasets to support decision-making. Specifically, optimal data strategies align to organizational strategy and serve to direct data management value chain activities (data gathering, data controllership, data analysis and insight sharing) to support value creation through decision-making. Data strategies are operationalized through data governance policies and data management practices.

The Professional Accountant's Role in Data

A joint CPA Canada/IFAC paper exploring *The Professional Accountant's Role in Data* (April 2021) describes how a CPA can ensure that appropriate data is used in value creation activities. Of note, there are times when the data may not align to expectations when analyzing an opportunity. Decision-makers need to understand that it takes time and money to gather and clean data. There are times when the opportunity will have passed if more data is sought before making a decision. Conversely, making a decision with inappropriate data can expose an organization to significant risks. Cost overruns and legal risk as privacy legislation changes are two examples; other risks exist. Care must be taken when using data not aligned with the organization's data strategy and data governance approaches. The image below summarizes the concepts described in *The Professional Accountant's Role in Data*.

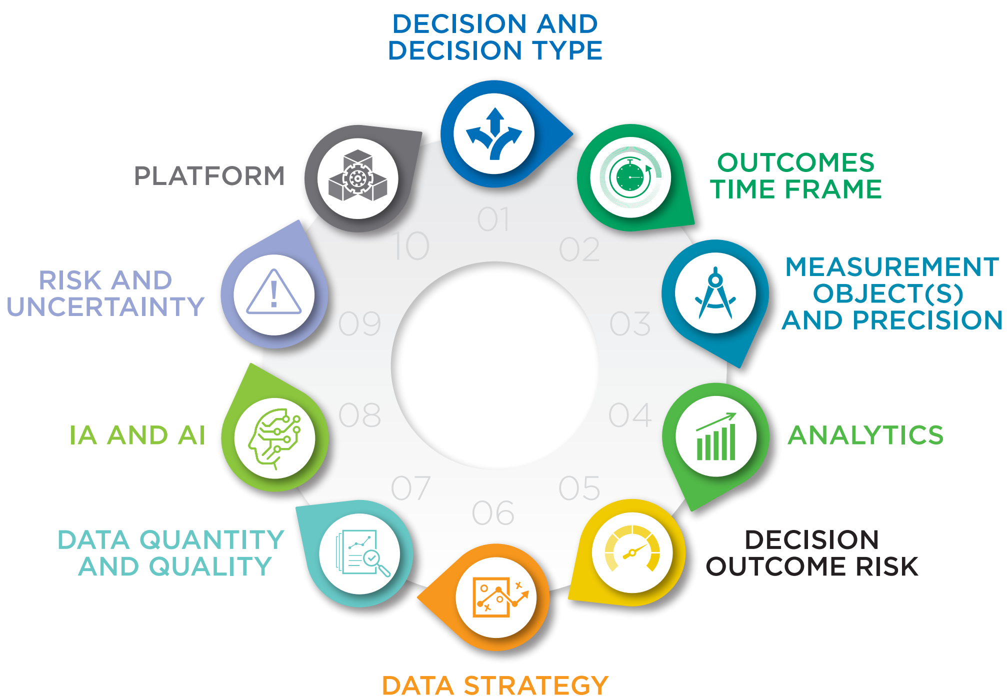


CPAs have an important role to play in each of the eight processes required for a comprehensive and optimal use of data to support value creation:

- data gathering – establishing what data should be gathered to support the organization in achieving its strategic objectives within the policy framework established through data governance while ensuring that the data is fit for purpose
- data controllership – ensuring that the "golden thread" of the data can be traced to make sure that the data is verifiable, used for its intended purpose, secure and used for only legitimate purposes by authorized individuals
- data analysis – confirming that the analysis is credible, verifiable and repeatable while ensuring that any assumptions underpinning the model are disclosed
- insight sharing – ensuring that the insights are appropriately contextualized and sourced, their provenance is certified and their intended use is documented
- data management – storing, gathering, organizing and maintaining data created, collected, purchased or otherwise secured by the organization to ensure it is fit for purpose when it is incorporated into models
- data governance – ensuring the availability, visibility, integrity and security of data in enterprise systems based on internal policies that control data usage
- data strategy – identifying the intent and use of data to generate revenue directly or to enhance decision-making through the development of data-driven insights
- organizational strategy – doing everything the organization intends to do to achieve its goals and objectives, including a detailed assessment of what it needs to do to get there

2. Building a decision support model: Ten factors to consider

The graphic below outlines 10 factors that a CPA should consider when designing and building a model to support a specific decision.



The following sections provide a commentary on each of the 10 factors.

2.1 Decision and decision type

The first step is to clearly define the decision the business needs to make. We can differentiate among four types of decisions: (1) one-time strategic decisions, (2) periodic strategic decisions, (3) one-time operational decisions and (4) routine operational decisions.

Decision type	Non-recurring	Recurring
Strategic	One-time strategic decisions	Periodic strategic decisions
Operational	One-time operational decisions	Routine operational decisions

- one-time strategic decisions
  When the consequences of making a bad strategic decision are significant, a business decision support model can clarify possible outcomes and the factors that will most influence the actual outcome. Examples include the following:
  — evaluating the potential outcomes of a new strategy
  — evaluating the potential outcomes of a significant investment of resources
  — evaluating the potential consequences of an emerging strategic opportunity or threat

- periodic strategic decisions
  When there is an opportunity to optimize periodic strategic decisions, many of which are made on an annual basis, a model can be useful. Examples include the following:
  — selecting R&D projects for funding – what is the likely opportunity to monetize the research
  — evaluating business unit performance
  — updating annual business plans
  — performing portfolio analysis to develop more sophisticated risk management approaches across the entire organization, not only within a business unit

- one-time operational decisions
  While in many cases it may not be worthwhile to build a model to support a one-time operational decision, there are circumstances in which a skilled analyst with a relevant dataset could quickly develop a model that would incorporate key input factors to develop relevant data-driven insights to support a one-time operational decision. The key issue is materiality: If building a model costs $10,000 to develop, one would wish to be confident that the likely net benefits of making a better decision significantly exceed that cost.

- routine operational decisions
  When there is an opportunity to increase the likelihood that routine high-value operational decisions are made in an optimal way, building a data-driven model can be extremely cost effective. For example, the U.S. Army adopted a custom-built model to optimize the distribution of vehicles to ensure the right vehicle with the right configuration was delivered to the right client at the right time within a series of order lead time, build and transportation network constraints. Other examples include the following:
  - day-to-day credit decisions in a financial institution
  - day-to-day process scheduling decisions in a manufacturing operation
  - demand-sensitive pricing

2.2 Outcomes time frame

A second key factor that influences the design of a model is the time frame within which the outcomes will occur. In general, the longer is the time frame, the greater is the level of uncertainty that the model needs to be designed to manage. In traditional business decision contexts, we can differentiate among short, medium and long time frames as follows:

- short: less than one year
- medium: one-five years
- long: greater than five years

2.3 Measurement object(s) and precision

The measurement object(s) that the model works with have a significant impact on complexity, validity and precision of the model outputs.

- financial/single domain: In a business decision model that focuses on only financial outcomes (a single-domain model), the measurement object is typically expressed in currency based on transactions. This simplifies the inputs, assumptions and calculations.
- multi-domain: A model that focuses on financial and non-financial outcomes (a multi-domain model) must incorporate a broader range of inputs, such as a model that integrates factors related to technology and sustainability in addition to financial inputs.

In both cases, attention must be paid to measurement fundamentals to ensure that the reliability of data inputs and validity and precision of model outputs are sufficient to support the needs of the decision-makers.

2.4 Analytics

Model design will be influenced by the extent to which it employs one or more of the following analytics categories:

- descriptive: analysis that provides insights into past outcomes, such as analysis of historical results to define different levels of performance outcomes
- diagnostic: analysis that provides insights into why past outcomes occurred, such as analysis of historical results that provides insights into the factors that contribute to different levels of performance outcomes
- predictive: analysis that provides insights into possible future outcomes, such as analysis possibly combined with machine learning that provides insights into potential future performance, accompanied by an assessment of the most significant opportunities and risks from a financial and operational perspective
- prescriptive: analysis that provides insights into the factors that drive possible future outcomes and into actions that could be taken to maximize the odds of desired future outcomes (Prescriptive analysis can be combined with machine learning, such as in a model designed to identify bottlenecks in a manufacturing process and assess the effectiveness of alternative initiatives to overcome those bottlenecks.)

2.5 Decision outcome risk

An important factor influencing model design and the resources allocated to develop the model is the perspective from which we are looking at risk and the level of risk attached to the decision outcomes.

Traditionally, most business models have looked at risk from the perspective of the organization. From this perspective, we can differentiate among the following levels of risk:

- low: This level applies where an organization is committing resources that are equivalent to less than five per cent of its assets or that could influence operating results by less than five per cent of future income.
- moderate: This level applies where an organization is committing resources that are equivalent to ~5-20 per cent of its assets or that could influence operating results by ~5-20 per cent of future income.
- high: This level applies where an organization is committing resources that are equivalent to ~20 per cent or more of its assets or that could influence operating results by ~20 per cent or more of future income.
- very high: This level applies in a "bet the company" situation, where the difference between getting it right and getting it wrong could mean the organization (1) survives and thrives or (2) risks its continued existence.

Note that even low-risk decisions can benefit from modelling. For instance, in a financial institution, risk of individual consumer credit decisions is low, but the impact of getting it right across thousands or millions of such decisions can have a significant positive impact on performance.

2.6 Data strategy

Modelling possibilities within an organization will be significantly affected by the availability of suitable data, which is, in turn, a function of the maturity of the data strategy in the organization. The maturity of an organization's approach to data strategy can be evaluated as follows:

- none: The organization does not consider data to be a strategic resource.
- ad hoc: The organization recognizes the importance of data as a strategic resource but does not have a formal data strategy.

- developing: The organization recognizes data as a strategic resource and has developed a data strategy to support revenue generation and/or decision-making. It has or is developing a data governance policy and a management framework.
- mature: The organization has adopted internal controls in relation to its data strategy, including documentation, testing and monitoring for effectiveness of key controls over data gathering, data controllership, data analysis and data insight sharing.

2.7 Data quantity and quality

For a given level of data strategy maturity, model design will necessarily reflect the quantity and quality of data available.

Quantity of data can be assessed as low, moderate or high.

- low: Data is collected as needed. The organization utilizes data to perform some decision-making processes and to conduct research ad hoc, but experience and subject-matter expertise are more highly valued in decision-making. Organizations with thick bureaucracy and little need for fast or efficient decision-making stand out as prime examples. Alternatively, organizations that possess low quantities of data may be entering into a new industry or venture, for which data sources are limited. In such cases, resources must be expanded to grow to medium and then to high quantities as efficiently as possible, while preserving the credibility of the data being collected.
- medium: Historical data is available though may not be continuous and is likely collected on fixed interval periods (i.e., months, quarters or years). The organization values data-driven analysis but may not rely on it for day-to-day decision-making. Large investments are vetted via analytical products that leverage the data, but industry expertise and manual processes still play a significant role in the decision.
- high: Historical data is readily available and collected on a routine basis as part of regular business practices. In these situations, the organization likely places a very high value on data-driven decision-making, and treats data as a commodity to be stored and leveraged efficiently. These examples may include financial institutions and firms that cater to “market makers,” or firms that rely on optimized business processes, such as logistics and manufacturing.

Data quality can be assessed as low, moderate or high.

- low: Firms that do not rely on data for daily decision-making likely will not place a high value on the credibility, applicability or curation of data, given the high costs and barriers associated with such tasks.
- medium: The data that is collected is accessible but may not be aggregated in the same format. The ease with which data can be used depends on its type: some datasets are easy to use while others are not. The data owners may accept some degree of uncertainty in the data, whether through the credibility of the data sources or the final state of the sources, which is accounted for via analytical means. The existence of the data takes precedence over the curation.
- high: As the quantity of data increases, so does the need for efficient storage and curation. Further, firms that value data-driven decision-making also place a high value on the accuracy of the data and ensuring reliable sources of the data, further improving the perception of quality. Data is typically cleansed, normalized and stored in efficient mechanisms that are easily accessible by those who need it.

2.8 AI and IA

The increasingly wide variety of various types of cost-effective machine-learning software means that anyone building a significant model must at least consider potential utilization of these techniques.

In so doing, we can choose to opt for Artificial Intelligence (AI), Intelligence Augmentation (IA) or, in some circumstances, both.

- AI involves fully automating a decision stream such that the decisions are made by a machine. For example, "[m]achine [l]earning algorithms are excellent at detecting transactional frauds by analyzing millions of data points that tend to go unnoticed by humans … [and] also [reduce] the number of false rejections and [help] improve the precision of real-time approvals." See "12 Use Cases of AI and Machine Learning in Finance".
- With IA, human judgment remains an essential component in the decision process, but technology is leveraged in such a way as to enhance human judgment by providing insights to the decision-maker that they would not otherwise have. As an example of IA in action, consider strategic risk identification.

Identification of strategic risk with AI

Excerpt from Cogito blog, August 20, 2021: Part 2: Key Benefits of Augmented Intelligence in Business
[A company called BlueDot] used augmented intelligence to be the first to spot COVID-19 before the World Health Organization's (WHO) in January 2020.

The outbreak risk software-as-a-service (SaaS) company uses Natural Language Processing (NLP) and Machine Learning (ML) as the basis for proactive augmented intelligence risk identification. BlueDot strategically culled data from sources across public health, travel, livestock industry health reports and population demographics among others. Their discovery played a critical role in understanding the spread of COVID-19.]

With either approach, but particularly AI, it is important to include fail-safes to ensure the outcomes remain strategically aligned.

The choice of AI, IA or both should be driven by the nature of the decision and by the degree to which that decision requires a perspective that is sensitive to nuance. The ability to leverage AI is highly dependent on the quantity, quality and relevance of available data. In the absence of sufficient clean data, the costs and other risks of deploying AI may exceed the benefits. Also, it is likely that the deployment costs of AI will be more easily justified for recurring decision streams.

AI and IA can be combined. For instance, where data is sufficiently structured, AI can analyze and organize that data, based on algorithms and business rules, into a form that can more effectively be used by humans to make appropriate strategic decisions.

2.9 Risk and uncertainty

Risk and uncertainty are inherent in any business decision support model that exists for the purposes of making decisions about the future. Techniques that are commonly used to manage that risk and uncertainty include scenarios, sensitivity analysis, probability distributions, etc.

When designing a model, it is important to consider the level of risk and uncertainty that exists, and consider the degree to which the model can incorporate approaches that manage or mitigate the risk and uncertainty.

Residual risks are the leftover risks that remain after all the known risks have been factored in, countered or mitigated. They can also be thought of as the risks that remain after a planned risk framework and relevant risk controls are put in place. Subtracting the impact of risk controls from the inherent risk in the business (i.e., the risk without any risk controls) is used to calculate residual risk. See *A Framework for Board Oversight of Enterprise Risk*.

To assist decision-makers to determine how much to rely on model outcomes, the following points show the way residual risk and remaining uncertainty can be categorized:

- low residual risk and uncertainty (such as modelling the impact to staff retention should employment conditions change through collective bargaining)
- moderate residual risk and uncertainty (such as anticipating production impacts of replacing equipment in an existing manufacturing plant)
- high residual risk and uncertainty (such as when developing a cost estimate to build ships in Canada when the industry has been dormant for 40 years, resulting in a lack of data to estimate the time and cost to build ships in Canada)

2.10 Platform

A model will almost always be built in some form of software. We can differentiate among four approaches along a continuum of technical sophistication:

- general purpose tools: use of spreadsheets and other general purpose tools, with development in-house or using outside experts
- specialist software: use of commercially available specialist software, usually with some technical support by a vendor or consultants
- custom AI: use of a custom-developed AI platform, usually developed with support by a vendor or consultants
- model management system (MMS): one or more of the above approaches combined with use of a model management platform that manages multiple models deployed within an organization to support various decision streams

3. Modelling long-term value creation: Impact on the 10 factors

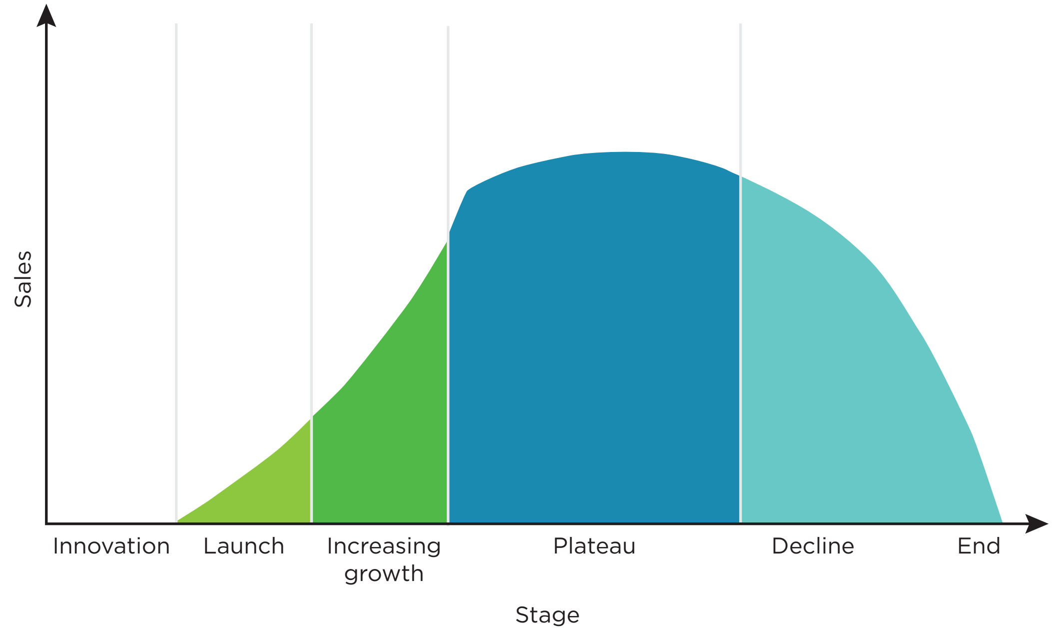
In today's context, a traditional business plan built by extrapolating last year's financial results over the next five years doesn't cut it as a means of supporting business decisions about the future. Financial projections based on past transactions are not sufficient to generate insights about future business outcomes.

In Section 1, we quoted CPA Canada's definition of value creation as follows:

> [The] process by which an organization generates, preserves or allows to erode future financial and non-financial value streams and outcomes for the organization and its stakeholders in an ethical and sustainable manner.
>
> [See *Leading the Way, Competency Map 2.0*, 29]

We can't measure future value creation based on past transactions; hence, we need to model it based on future value streams. The above definition asserts the following:

- Value streams modelled should include both financial and non-financial streams, recognizing that financial and non-financial value streams are frequently related.
- Value streams must be modelled both from the perspective of the organization and its stakeholders.
- The model should be designed to include relevant ethical and sustainability considerations.



Therefore, building a model that provides insights into future value creation potential requires the following steps:

- identifying long-term financial and non-financial value streams from the perspective of multiple stakeholders. Some of these value streams may be referenced in ESG disclosures. This may require prioritization, as stakeholders may have conflicting interest or perspectives:
  - long-term financial value streams, such as (1) net future revenue for the enterprise and (2) future economic benefits or costs anticipated for shareholders

- ecosystem value streams affecting the parts of the planet the business touches, such as progress toward "net zero" GHG emissions
- impact on health and well-being of employees and community members

See *Director Briefing – Stakeholder Engagement*.

- developing data inputs and assumptions that support modelling value streams over their full lifecycle, which is usually considerably longer than the traditional five-year business plan:
  - To be meaningful in relation to "net zero by 2050" goals, progress toward net zero must be visualized over a time frame of 25-30 years, leveraging relevant and credible climate models and scenarios.
  - Similarly, impacts on stakeholder health and well-being must be visualized over a long-term time frame.
  - Given these requirements, a business must be able to visualize its financial performance over similar long-run time frames.

- incorporating event-driven analytics referring to analysis involving the following:
  - All assumptions are linked to past or future anticipated events.
  - As events occur, the value streams and outcomes generated by the model are updated (automatically whenever possible) to reflect changes as assumed values are replaced by actual values.
  - The model is continuously extended into the future as additional future events and assumptions are added or linked

Modelling long-term value creation based on this approach requires that we modify the 10 factors discussed in the previous section as discussed below. The shaded areas in the following table identify modifications to the 10 factors influencing model design that apply when modelling long-term value creation.

Factors		Position on the continuum				
1. Decision and decision type		One-time strategic	Periodic strategic	One-time operational	Routine operational	
2. Outcomes time frame		Short	Medium	Long	Life cycle	
3. Measurement object(s) and perspective		Multi-domain		Multi-perspective		
4. Analytics		Descriptive	Diagnostic	Predictive	Prescriptive	Event-driven
5. Decision outcome risk	Organization	Low	Moderate	High	Very high	
	Stakeholders	Low	Moderate	High	Very high	
6. Data strategy		None	Ad hoc	Developing	Mature	
7. Data quantity and quality		Low	Moderate	High		
8. IA and AI		IA	AI	AI + IA		IA + AI
9. Risk and uncertainty		Moderate residual risk and uncertainty	High residual risk and uncertainty			
10. Platform		Specialist software		Custom-developed	Model management system	

The following paragraphs provide commentary on the shaded areas above.

3.1 Decision and decision type

The main implications for decision and the decision type when modelling value creation is the need to define the decision while keeping in mind the long-term perspectives of multiple stakeholders. The four decision-type categories are still valid (one-time strategic decisions, periodic strategic decisions, one-time operational decisions, and routine operational decisions), but the scope of the decision's impact is potentially broader.

3.2 Outcomes time frame

When modelling value creation, we need to think further ahead than 5-10 years and add a longer-term "life cycle" time frame that takes into account outcomes that extend 10-20 years or longer into the future. We now know that an organization's impact on the climate extends over many decades, as can effects on the health of individuals and communities. Depending on the decision, the life cycle in question could be for a technology, a product family or a specific product, a depleting resource in the case of extractive industries, etc.

3.3 Measurement object(s) and perspective

When modelling value creation, the relevant measurement object is future value streams, not past transactions. Since it is about the future, a model cannot be based solely on past data, but wherever possible, assumptions about the future should consider past data patterns as well as alternative future scenarios.

While a traditional business model could potentially focus on a single domain (financial) from a single perspective (the organization), when modelling value creation, it is essential to consider value streams that include multiple domains, reflecting multiple perspectives.

Quantity of input	Domain	Perspective
Single	e.g., financial	e.g., the organization
Multiple	e.g., financial, technology, sustainability, etc.	e.g., the organization, people, ecosystems, communities

In a value creation modelling context, it is still important to consider measurement fundamentals to ensure that the reliability of data inputs and validity and precision of model outputs are sufficient to support the needs of the decision-makers.

3.4 Analytics

Since modelling value creation is inherently about the future, we need to recognize the need for a new type of analytics that is event driven.

Event-driven analytics assumes a model in which all assumptions are linked to past or future events. Since assumptions are linked to future events, whenever an event that was formerly in the future has occurred, the model is updated to reflect the now-known outcome of that event. The outcomes driven by event-driven analytics are continuously updated (ideally on an automated real-time basis) as defined events occur and as the event horizon of the analysis is extended to include new future events.

3.5 Decision outcome risk

In considering decision outcome risk for a value creation model – while it is still valid to categorize risk along a continuum that includes very high, high, moderate, and low – a key change in a value creation context is that we need to explicitly look at decision outcome risk from multiple stakeholder perspectives in addition to the organization perspective. A potential outcome that has a low negative outcome risk from the organization perspective but has a high negative outcome risk from a stakeholder perspective must be considered a high-risk outcome.

3.6 Data strategy

When considering data strategy in a value creation modelling context – while it is still valid to assess the maturity of an organization's data strategy along a continuum that includes none, ad hoc, developing and mature – in making this assessment, CPAs should expand the scope of data to include that relevant to multiple stakeholders.

While an organization may have a “mature” data strategy as it relates to past transactions, in a value creation content it may be at a “developing” level, given the need for extensive use of non-financial data, externally sourced data and new technological approaches to integrate existing structured data and potentially massive amounts of unstructured data. The development of controls around the collection, cleansing, grading and stewardship of data are critical to ensuring (1) the data is fit for purpose and (2) the insights arising from models are credible and properly interpreted.

3.7 Data quantity and quality

The implication for data quantity and quality when modelling value creation is that the data reliability required for a decision is different from data reliability required for a disclosure. Disclosure has traditionally been based on past transactional data. However, business decisions about the future require data that is fit for purpose in supporting the decisions. Another way of stating this is data quality and quantity that is aligned to the decision point.

For example, “idea generation” can be based on estimates, “options analysis” can use indicative or directionally correct data, while a “go/no go” decision on a major investment requires more refined data. The purpose for which the data will be used is essential to understanding its quality. Sub-quality data may need to be used for some decisions because while it costs money and takes time to gather data, the decision point may be such that the decision has to be made now, and there is no more time to collect better data.

Quantity is also relevant. AI requires massive amounts of data to train, test and monitor the AI. In the absence of massive amounts of data, decision-makers cannot be certain the AI is appropriately trained and is making decisions in accordance with the embedded business rules. Conversely, IA requires sufficient data to develop a credible and defensible model aligned with the value creation decision point.

Value creation uses forward-looking assumptions. Decisions are often unprecedented and usually not supported by a large volume of reliable data. An organization may want to change its approach to risk management and accept a certain nimbleness in the supporting data, compared to usual value realization paradigm.

3.8 AI and IA

Since a value creation model is future oriented, it will normally be necessary to use human judgment to assess the future-oriented inputs and assumptions, and the resulting model outcomes, which in general rules out pure AI approaches for value creation decisions. Ideally, wherever possible and subject to data availability, value creation models will use an IA-based approach to generating insights, supported by AI-based analysis of past data.

3.9 Risk and uncertainty

Since value creation models are future focused, risk and uncertainty are inherently higher than those with traditional models. In a value creation context, residual risk and uncertainty will usually be moderate or high. It is therefore essential to incorporate techniques such as scenarios, sensitivity analysis, probability distributions, combined with event-based analytics to obtain insights into the risks and uncertainties associated with the outcomes generated by a value creation model.

3.10 Platform

The technical alternatives for value creation modelling are largely the same as for traditional models. However, in general, the realistic platform options for value creation modelling are skewed to the right, since the technical sophistication required in most cases cannot be handled by general purpose tools.

4. Building modelling capabilities: A continuum

The discussion in Sections 2 and 3 above present a framework intended to assist CPAs to design a modelling approach to support a specific business decision. Section 2 deals with business decisions in general; Section 3 more specifically with value creation–related business decisions.

Most organizations that adopt modelling will do so intending to support multiple business decisions, not just a single specific decision. In this situation, it is important for the organization to adopt a strategic perspective on building modelling capabilities in the organization.

The chart below is intended to help organizations identify the status of their current modelling capabilities and recognize whether there is a need to evolve those capabilities over time.

Modelling capabilities continuum

Factors	Basic	Intermediate	Advanced	State of the art	Pioneering
1. Decision type	Non-recurring				Recurring
2. Outcomes time frame	Short	Medium	Long		Life cycle
3. Measurement object(s)	Single domain / Single perspective				Multi-domain / Multi-perspective
4. Analytics	Descriptive	Diagnostic	Predictive	Prescriptive	Event-based

Factors	Basic	Intermediate	Advanced	State of the art	Pioneering
5. Decision outcome risk	Low risk	Moderate risk	High risk		Very high risk
5.1 Perspective	Organization				Stakeholders
6. Data strategy	None	Ad hoc	Developing		Mature
7. Data quantity and quality	Low		Medium		High
8. IA and AI	IA		AI		IA and AI
9. Risk and uncertainty	Low		Moderate		High
10. Platform	General purpose tool		Specialist software	Custom AI	MMS

We identify five positions along the Modelling Capabilities Continuum.

- basic: Organization has the ability to develop single-domain (financial) models from the organization's perspective to support short-, medium- and long-term non-recurring decisions employing descriptive and diagnostic analytics using limited (low quantity / quality) data. Models are built using mainly general purpose tools.
- intermediate: Organization has the ability to develop single-domain (financial) models from the organization's perspective to support short-, medium- and long-term non-recurring and recurring decisions employing descriptive, diagnostic and predictive analytics using low-medium quantity / quality data. Models are built using mainly general purpose tools with some use of specialist software.
- advanced: Organization has the ability to develop and maintain single and multi-domain models reflecting the organization's and stakeholder perspectives to support short-, medium- and long-term, as well as life cycle non-recurring and recurring decisions employing descriptive, diagnostic, predictive and prescriptive analytics using medium quantity / quality data including use of IA and AI for some types of decisions. Models are built using mainly specialist software and custom AI.

- state-of-the-art: Organization has the ability to develop and maintain single and multi-domain models reflecting the organization's and stakeholder perspectives to support short-, medium- and long-term, as well as life cycle non-recurring and recurring decisions employing descriptive, diagnostic, predictive and prescriptive analytics using high quantity / quality data including extensive use of IA and AI for many types of decisions. Models are built using mainly specialist software and custom AI, with consideration being given to use of model management systems to support the developing modelling infrastructure.
- pioneering: Organization has the ability to develop and maintain single and multi-domain models reflecting the organization's and stakeholder perspectives to support short-, medium- and long-term, as well as life cycle non-recurring and recurring decisions employing descriptive, diagnostic, predictive, prescriptive and event-driven analytics using high quantity / quality data including extensive use of IA and AI for many types of decisions. Models are built using mainly specialist software and custom AI, and the organization is also well advanced with using model management systems to support the modelling infrastructure.

We encourage CPAs to use this continuum to identify their organization's current modelling capabilities and set priorities for enhancing those capabilities over time based on the organization's needs.

Appendix B includes several case studies illustrating application of the 10 factors and the modelling capabilities continuum.

Conclusion

CPA Canada's Foresight initiative highlighted the opportunity and necessity for CPAs to move beyond a traditional focus on financial transactions to place a new emphasis on value creation measured by broader financial and non-financial metrics, from the perspective of multiple stakeholders. CPAs have a leading role to play in improving the quality of models used by their organizations to support business decisions and assessing the capabilities of the vast range of modelling tools available in the market.

In this paper, we have explored how CPAs can support their organization's business decisions by designing modelling approaches that incorporate expectations about the future and help organizations anticipate and evaluate different financial and non-financial outcomes and impacts. The framework discussed in Sections 2 and 3 helps CPAs methodically consider the factors that are relevant to optimizing the design of models and transforming data into meaningful information to support value creation for organizations and their stakeholders. Finally, the modelling capabilities continuum in Section 4 will support the ongoing role of CPAs in strengthening their organization's modelling capabilities over time.

For further information, see Appendix A for links to documents, webinars and other online resources relevant to value creation and data governance. Also see Value Creation for links to professional education opportunities related to Modelling Value Creation in a Data-Rich World, including opportunities focused on value creation and data governance.

Appendix A: Recent CPA Canada Foresight-related initiatives

CPA Canada continues to work to transform and strengthen the CPA profession, based on the insights emerging from the Foresight process. Recent value creation–related initiatives include the following:

- publications:
  - CPA Canada. (February 2020). *Value Creation Decisions and Measurement Primer*
  - CPA Canada. (March 2021). *What Is Data Worth? Insights for CPAs*
- webinar: Introduction to Value Creation: Opportunities for CPAs
- online services: Global Value Creation Solutions Directory

In parallel, CPA Canada's Mastering Data Series of publications supports the role of CPAs in helping their organizations transition to a digital economy. Explore the full series or look at the selected documents below:

- CPA Canada. (October 7, 2020). Making Sense of Data Value Chains
- CPA Canada. (January 8, 2021). What Is Your Data Worth?
- CPA Canada. (August 2021). *Inject Trust Into Your Data-sharing Ecosystem*
- CPA Canada. (October 5, 2021). A CPA's Role in Ensuring Trust in Your Data-sharing Ecosystem

Also, value creation and data management are significant topics of the new competency map 2.0. This document sets the expectations for students interested in the CPA profession. In the near future, all newly designated CPAs will have acquired a level of proficiency in those areas. See CPA Canada. (2022). *Leading the Way: Competency Map 2.0*

Finally, value creation leads directly to a greater consideration for sustainability. An organization that assesses the outcomes of its activities for a broader range of stakeholders will inevitably consider its impact on communities and on the planet. CPAs are engaged into creating sustainable value for the organizations, and CPA Canada supports their journey via new resources accessible on the following page: Sustainability Is Good Business.

Appendix B: Case studies and commentary

Case study example 1

Organization: Provincial Government Agency

Description: In order to support funding decisions for technology-based solutions to reduce GHG emissions in the province and beyond, the Agency needed a modelling solution that was built into the online application and evaluation platform for its GHG-reduction funding program. Applicants were required to provide baseline data and future estimates. Based on that data, the underlying software platform generated instant projections of future environmental impacts and economic ROI for solution adopters.

Factors overview:

1. Decision	Description: Selection of innovation/technology solutions for funding that offer significant economic potential combined with significant reductions in greenhouse gas emissions Type: Strategic, recurring
2. Outcomes time frame	Life cycle (20 years or longer)
3. Measurement object	Value stream: economic return on investment Value stream: GHG emission reductions Perspectives: organization, technology adopters, province, Canada, international
4. Analytics	Predictive

5. Decision outcome risk	Focus on stakeholder impacts: economic and GHG reduction impacts at technology adopter / provincial / national / international level
6. Data quantity	Limited, model based mainly on future estimates
7. Data quality	Limited, model based mainly on future estimates
8. IA and AI	IA: Model used to provide insights for funding decisions
9. Risk and uncertainty	Mainly handled through scenario analysis: least favourable, most likely, most favourable
10. Platform	Approach: special purpose software Consulting support: yes

Model overview

Key model inputs (based on future estimates supported by past data where available):

- number of installations: province, Canada, international
- GHG emission reductions per solution installation
- annual change in incremental GHG impact over time
- acquisition cost to solution adopter per installation
- cost savings to solution adopter per installation
- estimated jobs impact

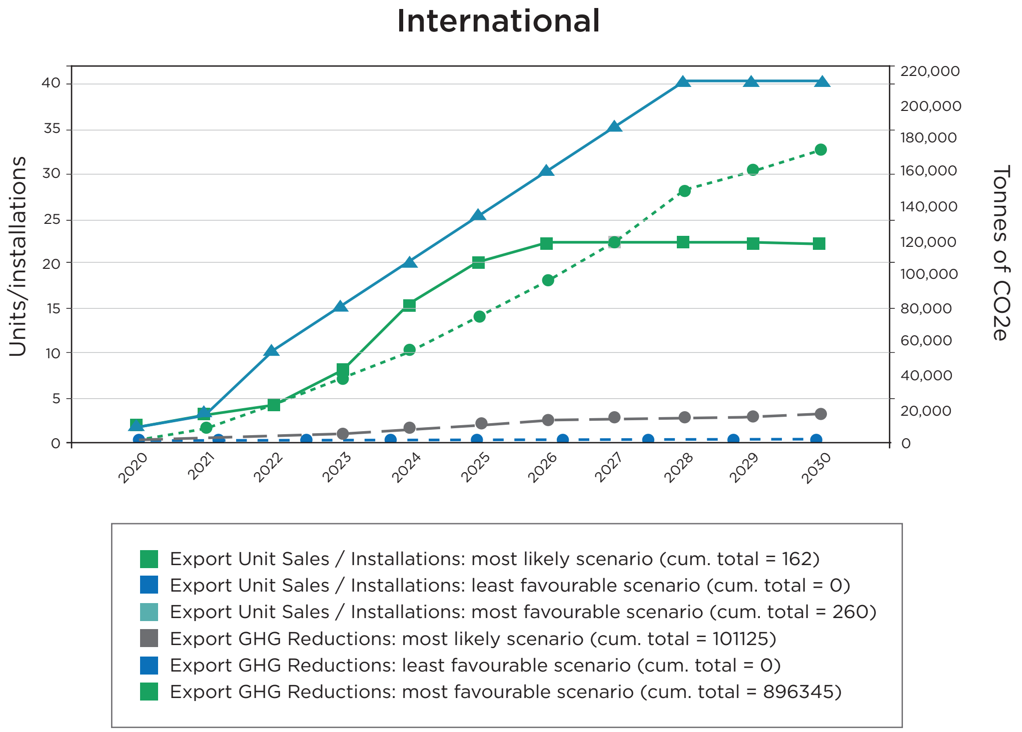
Key model outcomes

- projected emission reductions: province, Canada, international
- emission reductions relative to provincial funding sought
- 10-year ROI to solution adopters
- jobs impact

Examples of modelling outcomes

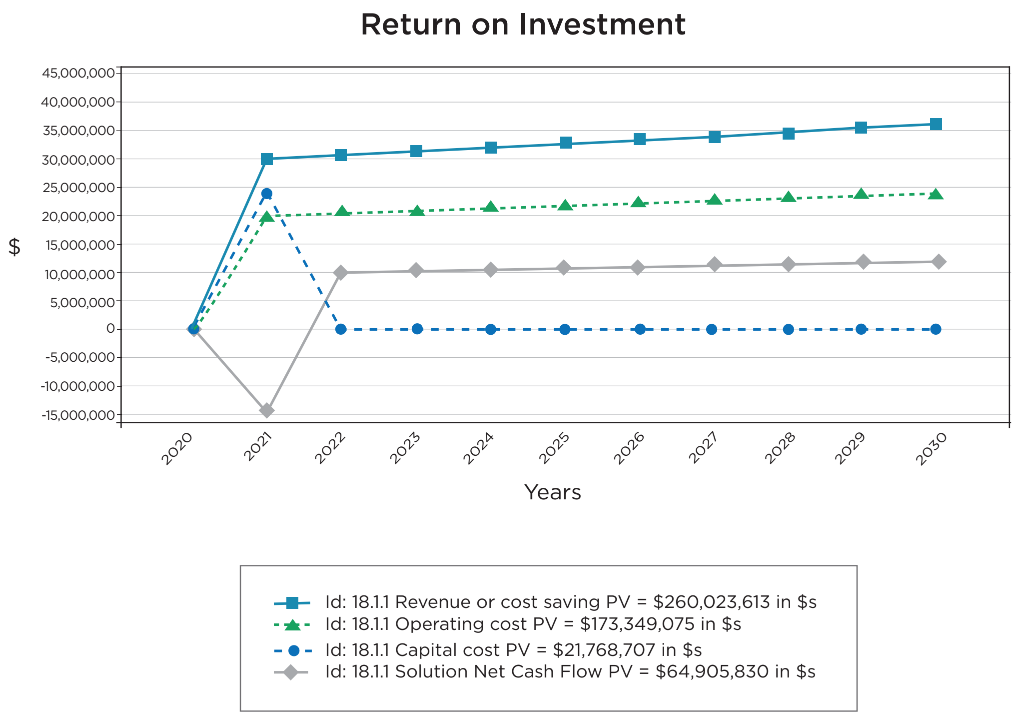
Commercialization roll-out exports

The following chart summarizes the estimated total emission reductions based on the projected unit sales or installations outside Canada (left axis), multiplied by the estimated annual emission reductions per unit or installations (right axis), after adjusting for the specified annual incremental change in GHG Impact over time.



Return on investment to solution adopters

The following chart calculates an estimated return on investment (based on a present value calculation over the lesser of the operational lifespsan or 10 years, using a five per cent discount rate) to an adopter of the solution who acquires the solution in 2021. The calculation takes into account the specifed cost of acquisition (capital cost), operating costs and any revenue or cost savings to the solution adopter.



Position in modelling capabilities continuum

Basic/Intermediate: The modelling approach included multiple domains (financial, ecosystem impacts) and predictive analytics, but the underlying data was limited. The models were generated on a specialized online platform, with consulting support, based on applicant submissions and expert reviews.

Case study example 2

Organization: International pharmaceutical company

Description: Like its peers in the pharmaceutical industry, the company had a physician education (PE) unit dedicated to providing physicians with the required knowledge to assess when to prescribe a drug for a specific health indication and how to do so safely and effectively. Given the company's drug portfolio, it needed a way of determining the optimal allocation of PE efforts across the portfolio.

There are multiple factors that determine the optimal level of PE activity for a specific drug. A model was developed that accepted inputs related to these factors and calculated for each drug in the portfolio the incremental revenue, ROI and payback associated with alternative levels of investment in PE activities.

Factors overview:

1. Decision	Description: allocation of resources to physician education initiatives for various drugs in the company's portfolio Type: strategic, recurring
2. Outcomes time frame	Life cycle (20 years or longer)
3. Measurement object	Value stream: revenue Perspectives: organization
4. Analytics	Prescriptive, event-based
5. Decision outcome risk	Potential impact on market potential of drugs if over- or under-investing in PE initiatives
6. Data quantity	Moderate
7. Data quality	Moderate
8. IA and AI	IA: model used to provide insights for resource allocation decisions
9. Risk and uncertainty	Mainly handled through scenario analysis based on alternative resource allocation levels
10. Platform	Approach: special purpose software Consulting support: yes

Model overview

Key model inputs

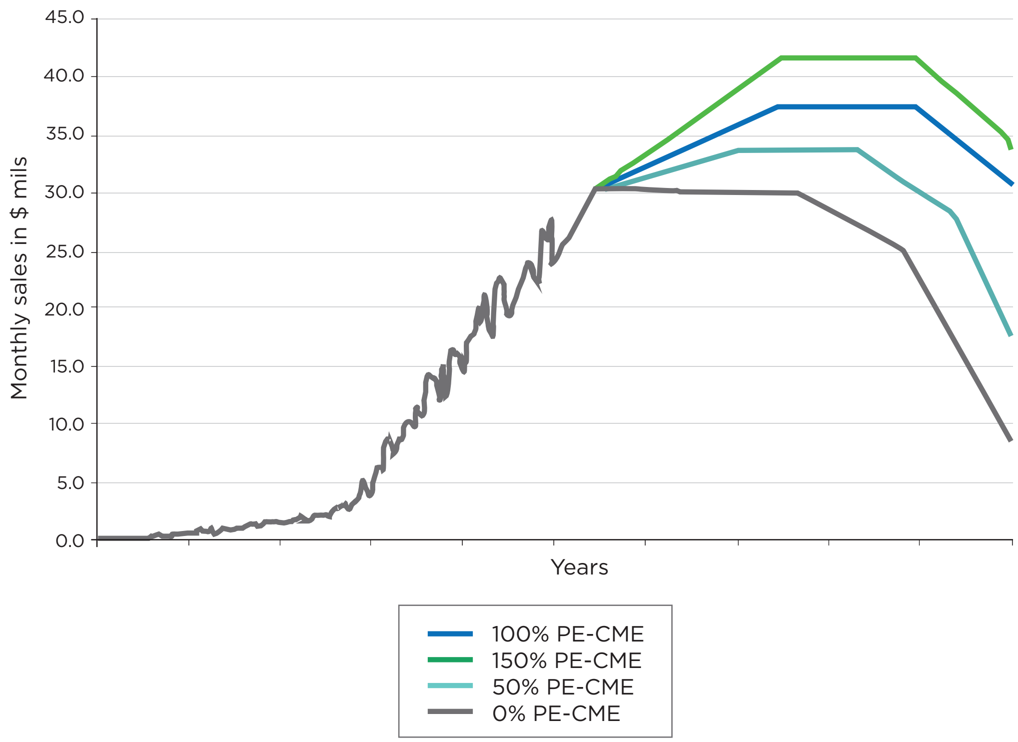
- historical sales and financial performance for each drug
- positioning of each drug relative to a framework of 18 strategic variables relating to the market position of the drug, therapeutic effectiveness relative to alternatives, and factors affecting the ability of PE to influence prescribing behaviour
- alternative PE spend levels

Key model outcomes

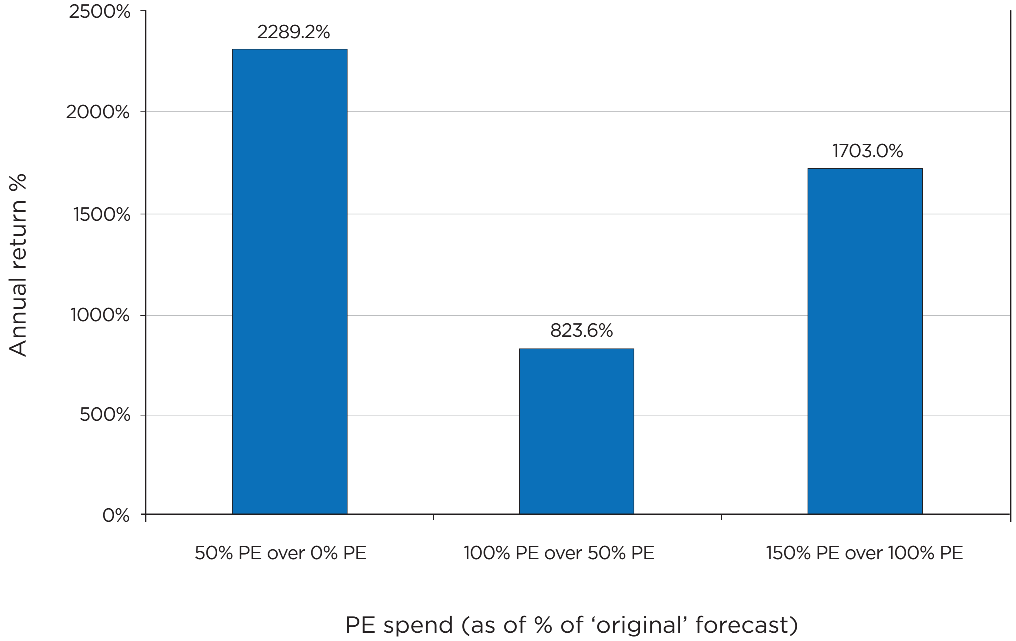
- revenue impact of alternative PE spend levels for each drug
- payback and ROI per $1 of physician education spend

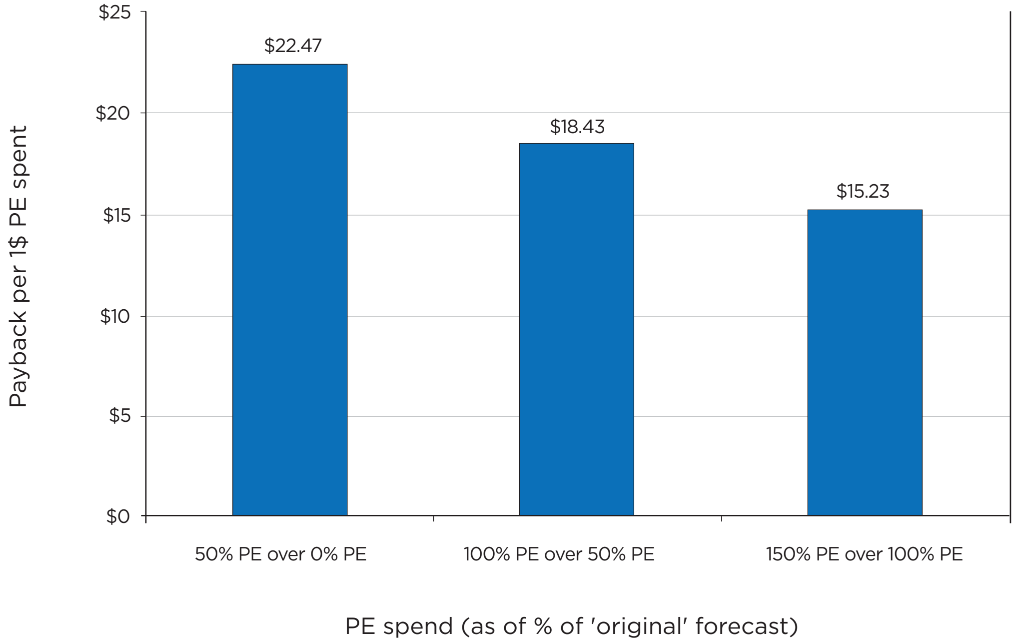
Examples of modelling outcomes

The following chart visualizes the future revenue curve for a specific drug, assuming alternative levels of PE investment.



The charts below show the estimated ROI and payment for each incremental dollar of investment in PE activities for a specific drug.





Position in modelling capabilities continuum

Intermediate/advanced: The modelling approach was primarily focused on financial impacts but incorporated multiple factors from a life cycle, event-driven, predictive perspective. The underlying data included historical performance, as well as consensus-based inputs generated through multiple expert workshops. The models were generated on a specialized software platform with consulting support.

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