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SPECIAL FEATURE:
Decision Intelligence

A Case for a More Decision-centric IBP

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PREVIEW *In his previous* Foresight *article (Issue 70), Niels van Hove wrote that although Integrated Business Planning (IBP) is designed to make high-impact business decisions, little attention has been given to the quality of decisions in an IBP cycle. In this article, he argues that to continuously learn from and improve IBP decisions, decision processes ought to be integrated with the traditional IBP process and supported by Decision Intelligence technology that goes beyond existing transactional and planning technology.*

Ultimately, a company's value is just the sum of the decisions it makes and executes.

— Blenko and colleagues (2010)

A LACK OF FOCUS ON DECISION QUALITY

In 1960, just 6% of jobs required core decision-making skills, where by 2018 this number had reached 34% (Agrawal and colleagues, 2022). Decisions and decision practices are clearly important, but has decision quality substantially improved? Managers and executives seem to think so, per surveys by McKinsey (Aminov and colleagues, 2019; Lovallo and Sibony, 2010). However, in my career I have never encountered a formal executive decision approach to improve decision quality. Hence, the McKinsey surveys more likely show that managers have little factual knowledge about the quality of their decisions.

IBP is first and foremost an executive decision-making process. The IBP team facilitates a structured, sequential, recurring monthly dialogue to align executive decision makers, functional leaders, and subject-matter experts – all to make critical business decisions. The IBP process supports a continuous rolling forecast, enterprise resource reallocation, and strategic alignment. Outputs of IBP can keep employees informed, engaged, and focused on executing strategy (van Hove, 2017). One would therefore expect a rigorous focus on high-quality decision making in IBP. However, one study of 500 managers and executives found that only 2% regularly apply structured practices when making decisions (Larson, 2016).

A DECISION QUALITY FRAMEWORK

A decision quality framework is described in the book *Decision Quality* (Spetzler and colleagues, 2016), based on the pioneering work of Ron Howard (1966)). Figure 1 shows the framework with six proposed elements of decision quality:

Appropriate frame. "What problem or opportunity are we addressing? Why are we doing it? And why now?" An appropriate frame includes a clear purpose, success metrics, a diverse perspective, and a well-defined scope.

Creative alternatives. A decision is only as good as its best alternative. Without alternatives, a decision isn't really a choice. There needs to be a manageable set of choices that are creative, significantly different, feasible, and compelling.

Meaningful reliable information. Quality information must be both relevant and reliable for the decision at hand. It must be within scope, support the anticipation of value outcomes for alternatives, and be drawn from accurate, unbiased, trustworthy sources.

Key Points

- Although the reason for IBP is to make impactful business decisions, little attention has been given to improving IBP decision quality.
- Decision processes ought to be included in the monthly IBP cycle to create higher-quality decisions, reduce analytics waste, and increase employee engagement.
- Decision Intelligence technology can help orchestrate IBP decisions by using a digitized decision process to augment the human factor, capture decision context, and facilitate decision learning.

Clear values and trade-offs. To reach clarity about which alternative we prefer and why we prefer it, we have to clearly articulate what we want and how to compare alternatives.

Logically correct reasoning. Choosing the best alternative for simple or repetitive decisions might be easy and done based on experience. Complex decisions require much more rigorous analysis, a decision model that incorporates all inputs, relationships, dependencies, probabilities, and values of any possible output combination.

Commitment to follow through. A decision isn't truly made until resources have been irrevocably allocated to its execution. We need to shift our mindset from thinking to doing, and clearly define what team and resources are going to execute the decisions.

Figure 1. Decision Quality Framework

The authors argue that to measure decision quality, one can score all the six elements between 0% and 100%. The lowest score is the weakest link and will define the quality score of the decision.

Applying this model means that even when decision makers believe they have applied perfect logic to solve the right problem, used reliable data to establish clear decision value, and are committed to action, if there have been no decision alternatives and the score for this quality element is 20%, then 20% would be the overall quality of the decision made.

A forecaster's or planner's role in improving IBP decision quality as per **Figure 1** is to frame the problem correctly, understand the company goals, provide decision alternatives using meaningful and reliable information, and, lastly, to provide explainability and understanding in the math used in the alternatives, in order to display logically correct reasoning to the decision makers.

Although a high-quality decision does not guarantee a high-quality outcome, using a decision-quality approach consistently should ensure that, over time, decision quality will improve for a company. While the best strategy is frequently twice as valuable as the good-enough strategy (Spetzler and colleagues, 2016), information is often imperfect and context changes, so the "best" decision may change over time. Thus, the capacity to reevaluate decisions would be a valuable capability.

DECISION TYPES AND DECISION MODELS

We should be able to improve decision quality across any decision type. I previously separated decisions into operational, planning, strategic, and cultural decisions (van Hove, 2021). These decision types can be differentiated between machine-centric Sales & Operations Execution (S&OE) decisions in the short-term horizon and human-centric IBP decisions in the longer-term (van Hove and Reeger, 2021).

To improve decision processes and decision quality, organizations must develop an understanding of decision models that support different decision types, explore if they are a cultural fit and provide value, and seek to integrate them in their operating model.

Operational decision model. The Observe, Orient, Decide, Act (OODA) loop is a decision process developed by United States Air Force Colonel John Boyd, who applied it to combat situations. It best serves short-term, fast, and agile decision making relevant to the S&OE horizon. We are starting to see examples of the OODA loop being applied to supply chain decision making (Geary, 2023).

Strategic decision model. The Causal Decision Diagram (CDD) visualizes decision choices, levers, external influencers, actions, and outcomes. It captures how humans naturally think about complex strategic or unique decisions (Pratt, 2019). The Decision Intelligence Navigator guides a user through decision context, appropriate framing, and intelligence access, hereby structurally addressing decision-quality elements (Moser, 2021). These models can support strategic questions like: Shall we enter a new market? Shall we rationalize our manufacturing footprint? Shall we acquire this company?

Planning decision model. In between the few strategic decisions and the enormous number of operational decisions a business makes each year, IBP addresses planning decisions like: Shall we adjust production capacity, inventory, service levels, or product price? Shall we introduce this new product or increase promotional intensity? Which vendor shall we select?

Research into the decision IQ of 160 companies revealed that businesses that follow checklists, inclusive decision making, and structured frameworks for high-quality decision making will consistently deliver strong decision outcomes (Larson, 2023a). Companies with such results almost always applied strong decision processes. The research used a decision framework that covers many quality elements and combines process steps, execution, and learning as per **Figure 2** (Larson, 2023b).

The Larson research indicates that integrating a planning decision framework with the IBP process can start to improve decision making in the IBP cycle. Additional benefits of good practices are making decisions twice as fast with half as many meetings (Larson, 2017) and positively impacting employee engagement through direct involvement in the process (Robinson and others, 2004).

Addressing Inherent IBP Decision Bias

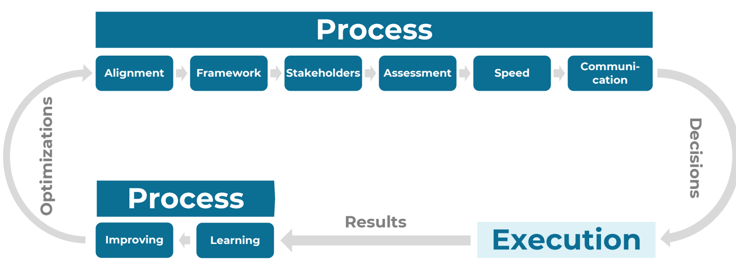
Based on their combined experience, Spetzler and colleagues (2016) identified five mega-biases that are threats to good organizational decision making: narrow framing, dragging problems in our comfort zone, confidence bias, the agreement trap, and the advocacy/approval myth. These last two mega-biases seem to be incorporated in IBP by design.

Agreement trap. This mega-bias confuses agreement with a good decision. There is a high focus on reaching consensus in meetings where the IBP teams advocate their recommendations.

Without rigorously challenging the quality of a decision, we might end up with a consensus as defined by Margaret Thatcher: "*The process of abandoning all beliefs, principles, values and policies in search of something in which no one believes, but to which no one objects.*"

Advocacy/approval myth. The mistaken belief that a quality decision can be reached by relying on powerful advocacy and intense questioning.

Figure 2. Decision IQ framework



Source: Cloverpop Decision IQ Benchmark Survey, 2023.

Advocates of certain recommendations will try to influence the IBP manager to shape the IBP deck to their agenda. Before they are presented to executives, such recommendations should be challenged through focus on the six decision quality elements. So should any intense questioning by executives during the IBP meeting, before they make a decision.

As we are "predicatively irrational," a consistent use of a decision framework, or even a simple decision checklist, can counteract human decision bias (Larson, 2016), increasing decision quality. Organizations are wise to develop a better understanding of these and other biases and integrate decision processes in IBP to prevent them.

A NEED FOR DECISION INTELLIGENCE TECHNOLOGY

I previously highlighted the need for a third wave of integrated supply chain planning software (van Hove, 2019) that goes beyond Wave 1, Enterprise Resource Planning (ERP), and Wave 2, Advanced Planning Systems (APS). This holds true to support faster and higher-quality IBP decision making.

ERP systems are often referred to as a "system of record" for enterprise data, as they hold a history of all master and transactional data. They support decision quality by providing meaningful and reliable information as input. These days, every self-respecting company will have an equivalent of an ERP system.

APS supports better IBP decision quality by providing high-quality alternatives, using Monte Carlo simulations, what-if scenario planning, and by using probabilistic forecasting and planning to predict decision outcomes and impacts. Many forecasters and planners already use these types of technologies as input for IBP decision making.

Although both ERP and APS systems support forecasters and planners to impact decision quality, they are focused on the inputs like data, analysis, insight, forecast, plans, or scenarios – not on the decision itself. Regeer and I (2021) suggested that IBP decisions and their impacts would need to be digitally recorded, transparent, and accessible for all IBP stakeholders to be able to learn from decisions.

To further support IBP decision quality, decision intelligence technology should treat decision making as a measurable business process as per Figure 2. The steps, the decision itself, the decision maker, the value, the impact, and the context are all data points that can be digitized, analyzed, and learned from. This creates a system of record for decisions.

When the process and the decision are treated as data points and stored in a system of record, a decision memory can be created. Machine learning or other techniques can then be applied to estimate the likelihood of success and impact, and augment a decision maker accordingly. For frequent S&OE decisions, we already see examples where decision intelligence technology provides a user with both a recommendation to change a source of supply, a mode of transport, a stock transfer order, or a safety stock setting, but also the probability of successful impact when accepting this recommendation. Over time, less frequent IBP decisions are likely to follow this example of "learning" from decisions.

These types of capabilities can only be provided by technologies that are built around the decision. The average forecaster or planner will understand that the Wave 1 or Wave 2 technologies they are working with can't provide these decision capabilities. Luckily, the first providers of decision-intelligence technology have arrived, and we'll see an acceleration of these types of technologies in the coming years.

We can expect numerous change hurdles in the adoption of this new type of human-machine decision making. To guide this evolution, companies that adopt Decision Intelligence technology need to adopt a new shared vision and create an AI-collaborative culture (Sanders and Woods, 2021). On an individual level, planners and forecasters need to develop their own mindset to accept and embrace the role of the machine and this new type of collaboration (van Hove, 2021).

CONCLUSION

Long overdue is a focus on decision quality in the IBP cycle. Improved decision quality can be achieved through an integration of decision processes and checklists, supported by decision-intelligence technology that digitizes the decision process to create a system of record. Using this approach, the IBP process will make faster, higher-quality decisions, while reducing analytics waste, increasing employee engagement, and continuously learning from decisions.

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How Decision Intelligence Integrates Forecasting, AI, and Data into Complex Decisions

LORIEN PRATT, DAVID ROBERTS, NADINE MALCOLM, BRIAN FISHER, KATIE BARNHILL, DANIELA JONES, AND MICHAEL KUDENOV

PREVIEW *Decision Intelligence is the culmination of a variety of established and emerging disciplines that, when integrated, improve decision making. To support and improve high-impact decisions, Lorien Pratt and colleagues introduce the Causal Decision Diagram (CDD) as a generalized multidisciplinary integration framework. The CDD focuses on decision actions and outcomes, matching a widespread human mental model. The authors share a detailed use case in the agricultural industry, which demonstrates this framework's value for forecasters and, in return, the prominent role forecasters can play in contributing to decision intelligence using CDDs.*

MOVING BEYOND DATA, FORECASTING, AND PLANNING

Decision Intelligence (DI) represents an inevitable next step in the increasing utility of data-driven technologies. "Big data" is just a raw ingredient, as organizations have moved into AI and similar "big model" approaches. Models alone are limited, however, and we're now moving to an era of "big decisions."

Models of the future have been dominated by planning and forecasting. DI builds on these models with a new approach, modeling the causal chains set in motion by actions available to decision makers that lead to business outcomes. This mental model is intuitive for humans and creates a bridge to advanced technology (Pratt and Zangari, 2009).

DI provides a context for forecasts within the frame of decision makers' available actions, responsibilities for outcomes, and external factors that may be measured both before and after a decision is made. This action-to-outcome approach to DI was originally described by Pratt and Zangari (2008), who wrote that this framework is widespread in human mental models of decision making, yet not well connected to emerging data, AI, and other evidence-based decision-making methodologies and technologies.

Building on this work, Pratt and Malcolm (2023) describe DI as a frame of reference to integrate decision assets from a variety of disciplines. These include, but are not limited to, forecasting, data, AI, business intelligence, analytics, decision support, causal reasoning, decision analysis, statistics, randomized control trials, complex systems, digital twins, game theory, simulation, optimization, and econometrics.

Since forecasts and predictions are important assets in DI models, the field of DI needs great forecasters. Conversely, DI models provide a framework that describes the context of forecasts and predictions in decision making and formalizes mechanisms for connecting to other assets like AI and data. This formalization provides an opportunity for forecasters to play a more prominent role in business decision making (van Hove, 2023).

THE CAUSAL DECISION DIAGRAM

Central to our approach to DI is the Causal Decision Diagram (CDD), illustrated in **Figure 1**. This template was based on extensive interviews with stakeholders who are responsible for decision making in complex environments. The CDD captures, in visual form, a structure that is commonly described in words when decision makers try to explain a decision. The CDD is applicable in situations where the results of actions are not obvious, either due to their effects taking a long time to be realized, rapidly changing external circumstances, feedback and/or emergent effects in the path from actions to outcomes, or because of multi-link pathways from actions to outcomes. This is true for high-impact, strategic or unique one-off decisions, as well as for many repeated operational decisions.

A decision is characterized by a person's or team's available actions (their authorities) and outcomes (responsibilities) for a single decision. CDDs show actions on the left and outcomes on the right, and mirror human cognitive models of decision making (Skinner, 1953). Just as a GANTT chart is used for project planning, the CDD represents a formalism for a task that was previously done "invisibly" or only in text or conversation. Importantly, CDDs also represent a new formalism for those in the field of visual analytics developing new methods to maximize the cognitive understanding of decisions in complex environments (Zaimoglu and colleagues, 2023).

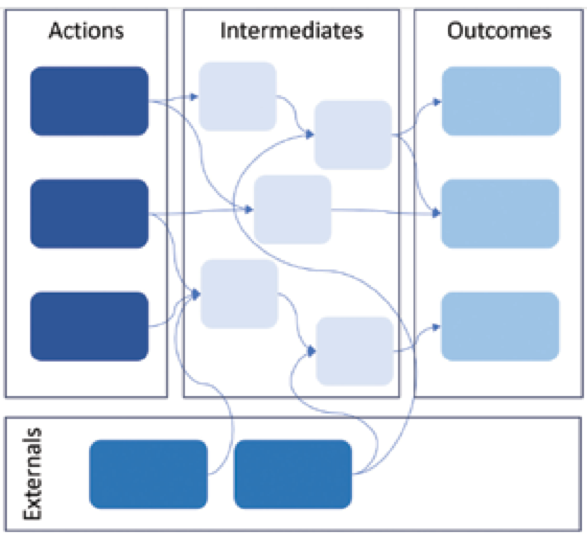
Core elements of the CDD

- **Actions and externals** are independent variables but serve different purposes. Both are inputs to models that lead to outcomes, but actions represent factors within the control of a decision maker, and externals are outside their control. An example is the difference between choosing the price of a product (an action) and the price selected by a competitor (an external).
- **Intermediates** are measurable elements along the causal chain from actions to outcomes, sometimes also called KPIs or metrics. Examples of intermediates might be the number of people in a particular demographic or the price of raw materials.
- **Outcomes** are the ultimate impact desired from the action. An example is the net revenue measured 24 months after a new price is set.
- **Causal Dependencies** are the arrows in the CDD, showing which intermediates and outcomes depend (in whole or in part) on which actions, externals, and/or other intermediates.

Key Points

- Decision Intelligence is a new discipline that goes beyond forecasting, planning, business insight, or foresight, and bridges the gap to improving action-to-outcome decision making.
- A Causal Decision Diagram (CDD) can be used to frame high-impact decisions, mirroring human cognitive decision models and improving stakeholder decision understanding and alignment.
- Once decisions are framed using a CDD, technology can be used to simulate decisions, allowing decision makers to test high-impact scenarios before making a final choice.
- The use of the CDD in an agricultural use case shows that forecasting remains a key asset to simulate decision options that support better decision making.

Figure 1. The Causal Decision Diagram (CDD) template, showing actions on the left, outcomes on the right, and intermediates in the middle, connected by causal dependencies. Externals — factors outside the control of the decision maker, but which affect the outcome — also connect to intermediates and outcomes.



Key characteristics of CDDs

- A CDD differentiates between predicting factors outside the control of decision makers (externals) and estimating the future impact of decision makers' actions that are under their control (the action-to-outcome flow).

- The CDD differentiates between planning, which is about choosing a series of actions to take in the future, and causal dependencies, which capture the causal chain of effects of actions.
- The CDD provides a model of how we think actions lead to outcomes in the world, rather than the flow of data through a system.
- The CDD is distinct from a decision tree, which uses various data fields to create another data field, such as health diagnostic information leading to a yes/no diagnostic decision. In contrast, the CDD shows the impacts of actions in some real-world system propagating through the world to create a business outcome.
- The CDD is distinct from information and insights required to support a decision. Pre-DI disciplines that provide information and insights include business intelligence (dashboards), AI (classifications, predictions, text summaries of information), statistics (models), and forecasting. The CDD goes one step further: from displaying information in helpful ways, to showing how that information informs the pathway from actions to outcomes.

The value of a CDD in big decisions

CDDs can have value simply as diagrams that formalize and align stakeholders around how a decision ought to be made. They have considerable extra value as a specification for decision simulation. Following the rich tradition of simulation used by the military, the Apollo space program, commercial airline pilots, medicine, and many other arenas, the CDD allows organizations to "crash the company in simulation" to avoid doing so in reality.

Take, for example, a European financial institution that our team is currently supporting. Facing a multi-billion-dollar pricing decision, this company has engaged a data warehousing team and a business intelligence group, and has spent seven figures to hire a consulting company to build machine learning modeling to predict the behavior of its customers, market, and macro factors that could affect its business.

However, despite the massive value of its decision, along with this organization's considerable assets, it has not yet integrated these expensive assets to answer the simple but critical question: "If we make this pricing decision that leads to this choice of price policy today, what will be the impact on our profitability tomorrow?"

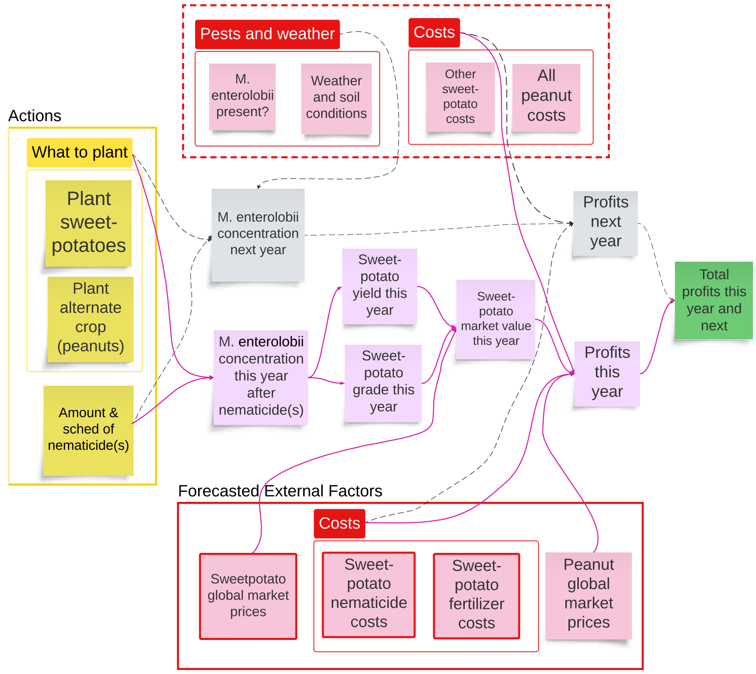
In this ongoing project, the CDD is providing a structured process and formal model to integrate all the company's assets to answer this multi-billion-dollar question.

A USE CASE IN AGRICULTURAL DECISION MAKING

Agricultural growers and produce packers face many dimensions of complexity and increasing volatility. These include constantly evolving market conditions with daily impacts of the price of goods and supplies; a changing climate as manifest in unexpected weather events; plus changing consumer attitudes, taxation, tariff, and subsidy volatility.

Many agricultural decision makers must select various actions (often multiple times per day), the effects of which aren't realized for weeks, months, or even years. For this reason, there is an increasing interest in the use of data and related technologies to inform decision making; the CDD can be used as an integration

Figure 2. An example CDD for sweetpotato production profitability, showing the role of forecasts and non-forecast external factors in the path from actions to outcomes.



framework to combine data, modeling, and human expertise into recommended actions that play out in nonobvious and complex ways. The CDD illustrated in **Figure 2** was developed by our team, in collaboration with stakeholders and subject-matter experts, in a study of the implementation of DI practices and technology innovations in sweetpotato supply chains.

Every spring, sweetpotato producers are faced with two decisions (among many) that are simple to articulate, but exceedingly complex to answer: "What crop do I plant?" and "What chemicals do I apply?" The action alternatives may be limited, e.g., plant sweetpotato or rotate to peanuts for a season, or pick from three alternative nematicide application schedules. But uncertainty about ultimate crop yields and market pricing won't be known for eight to 10 months, making these seemingly simple decisions very challenging. As illustrated in the CDD in Figure 2, external factors such as weather and input costs, for which forecast models may (or may not) exist, directly influence market values and profits. The presence and concentration of pests like nematodes, which are impacted by the choice of action, will further affect the ultimate outcome of profitability.

Growers make these choices in the context of four primary forecasts whose values are volatile: nematicide prices, fertilizer prices, peanut prices, and the market value of top-grade sweetpotatoes. Volatility is beyond the control of the producers (externals). This combination of multiple volatile externals makes for a complex decision that, with computer support, has the potential to substantially improve profitability for sweetpotato supply chain companies who can track these changes and adjust to this volatility in real time.

Critical externals that require predictions include not only customer demand and competitor behavior, but also supply chain volatility, the cost of raw materials, manufacturing costs, and transportation costs for raw materials and finished goods. An example is how the Panama Canal water shortage (Cohen, 2023) and its effects on transportation times and costs have forced many changes to pricing decisions.

This use case illustrates not only why DI needs forecasts, but also why forecasting also needs DI. The reason is that DI dramatically increases the value of forecasts. Here, the pesticide, fertilizer, and crop price forecasts by themselves provide insights; but the context of a CDD, along with other types of models like machine learning models to predict nematode concentrations based on crops planted, pesticides used, weather, and soil conditions, lets growers improve their action selections relative to their desired outcomes.

Simulating the CDD to determine the optimum pricing shows both the sensitivity of outcomes to each forecasted external and its "good" range of values that provides desired outcomes. This means that, even after the initial decision is made, the grower can continue to monitor forecasts of each external and have an early warning when it is drifting towards the edge or outside of its predicted "good" range. When such undesirable drift is detected, decision makers can use DI simulation that incorporates the current forecasts to find the best pricing and other choices to achieve their desired outcomes.

How to start your own CDD

Any forecaster or planner can start their own CDD and realize the benefits from it without extensive training or technology, following this process:

1. **Identify a decision to model.** Ideally one that requires a human in the loop, for which there is not enough historical data where it can be fully automated, and which takes place in a high-value and/or volatile, uncertain, complex and/or ambiguous (VUCA) environment.
2. **Agree on desired outcomes.** Work with a decision-making team—or on your own—to define things to measure (like net profit in 12 months) and goals (profits are over $20M in 12 months). Draw a list of these outcomes on the right-hand side of a diagram.
3. **Develop a list of available actions and choices.** Draw them on the left-hand side of the diagram (example: price to charge for a product).
4. **Develop a list of externals.** These are things you can measure but not control. They may be simple facts or forecasts. Draw them on the top or bottom of the diagram. For example, you might include your forecast of your competitor's price over the next 12 months, or your forecast of consumer demand for your product over that same time period.
5. **Develop intermediates.** In the middle, draw a list of intermediates (aka KPIs) you can measure as the actions play out through time to ultimately lead to outcomes. Double-check that neither your intermediates nor outcomes are process steps (actions you can take). They should, instead, be things you can potentially measure that are the consequences of the actions on the left-hand side.
6. **Add dependency arrows** between the items going mostly from left to right (although there is often at least one feedback loop), showing how actions will lead to outcomes through time.

Optionally, you might choose to ask a large language model like ChatGPT for new ideas for the above elements—especially unintended consequences you may not have considered—and add them to the diagram as you see fit (Pratt, 2023).

If you follow these simple steps, you'll have a basic CDD. Share it around the office, or even tape it to the wall, as a way to keep the team aligned around the rationale for their actions. Revisit the CDD frequently and update it to reflect new ideas and changes in your circumstances. As a next step, consider applying technology to simulate decisions, actions, and outcomes.

CONCLUSION

After decades of focus on business insights and foresights, DI bridges the gap from these disciplines to business decisions and actions. For many types of decisions in complex environments, the Causal Decision Diagram is a new approach to align, formulate, and display actions in the context of their outcomes and external elements like forecasts, and to simulate scenarios to make better decisions. The CDD provides the forecaster with a framework to maximize the value of their complex decision making, especially where data, AI, and similar technologies are available to simulate the best possible outcomes.

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