The Data-Driven Organizational Ecosystem: A Framework of Actionable Intelligence for Strategic Decision-Making

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Abstract: The proliferation of data impacts practicing managers in companies of all sizes and across all industries. To succeed, managers must effectively manage and utilize data to produce actionable intelligence. The Management Accounting Ecosystem (MAE) provides new and practical insights for professional managers. Building on the MAE, we describe the types of data available using the data creation spectrum. We then present the Data-Information-Knowledge-Actionable Intelligence (DIKAi) pyramid for developing actionable intelligence for strategic decision-making. Specifically, we provide examples of different types of organizational analytics that practicing managers can apply. Finally, we discuss how effective data sharing and utilization by practicing managers requires strong teamwork and leadership across the ecosystem.

Keywords: Actionable Intelligence; Data Analytics; Management Accounting Ecosystem; Teamwork; Leadership

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1. Introduction

Technological developments are constantly changing the business landscape. Accordingly, proper data handling, storage, and applications will play a major role in organizational success. Professional managers need to have access to relevant information and the proper context for what that information means for strategic management. However, without a proper framework for understanding data sharing, functional areas can be siloed and lack access to broader (other functional area) information, resulting in diminished decision quality.

The Management Accounting Ecosystem (MAE) provides professional managers with a framework on how to harvest, process, and store data from different areas of the company as well as other members of the company's broader "ecosystem", e.g., customers and suppliers. Success comes from not only leveraging internal data, but also from accessing and sharing information other members of the ecosystem. This ecosystem is situated within the context of laws, regulations, the broader economy, and even weather patterns. MAE shows how professional managers can use this information for strategic decision-making, which is all related to optimize decision-making.

The volume of information available is overwhelming if not properly processed. Building on the MAE's organization of ecosystem data, we describe the types of data available using the data creation spectrum and why this information should be stored in the company's accounting system. We then present the Data-Information-Knowledge-Actionable Intelligence (DIKAi) pyramid, a general framework for decision-making across the ecosystem, and describe how data analytics can help companies move up to the pyramid's pinnacle. Specifically, we describe how descriptive, diagnostic, predictive, and prescriptive analytics can address different business questions. Finally, adaptive and autonomous analytics provide ongoing solutions to meet the company's objectives. We provide examples of useful analytics techniques in the context of the supply chain.

Just understanding data analytic techniques is not enough, however. Gathering, processing, storing, and sharing data across a business ecosystem requires both teamwork and leadership. Therefore, we discuss the importance of teamwork in the context of the supply chain and data organization in general. Our goal is to provide a useful information to professional managers for organizing data sharing systems in enterprises of all sizes.

Coordinating among multiple organizations to gather, process, store, and share data requires both teamwork and leadership. We conclude by discussing the importance of teamwork in the context of the supply chain and data organization in general. This should serve as a useful framework for professional managers in organizing their data sharing systems in enterprises for strategic decision-making.

2. The data-driven view and the Management Accounting Ecosystem

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The information age has changed many of the fundamentals about the timing and nature of decisions in business. Most businesses now have access to far more data than any individual can collect and process on their own. Some of the data are extraneous and not decision useful, some are useful on their own, finally others are useful when put in the context of organizational goals and combined with other data. Identifying which data leads to better understanding of costs, profits, sourcing decisions, and can determine the success or failure of a business.

Figure 1 depicts a company's MAE. The MAE consists of raw data from the other members (such as Management, finance, marketing, engineering, and other functional areas) of a company's broader ecosystem, along with internally generated information. Data is processed by the accounting team in the technology layer and entered into the accounting system (AS). Accountants can make the information available to managers or be available to pull the needed information. The figure depicts information in the AS that can be useful for understanding a company's production model.

The accounting system is an ideal data repository because accountants already track labor, inventory, and other major costs for reporting, compliance, and decision making. The accounting system should already have high data integrity and security. Additionally, the accounting team understands the internally generated data well, while management accountants focus on making data decision-useful for management. These advantages allow the accounting team to curate data from other sources and quickly understand how to store it and who may use the data in the future.

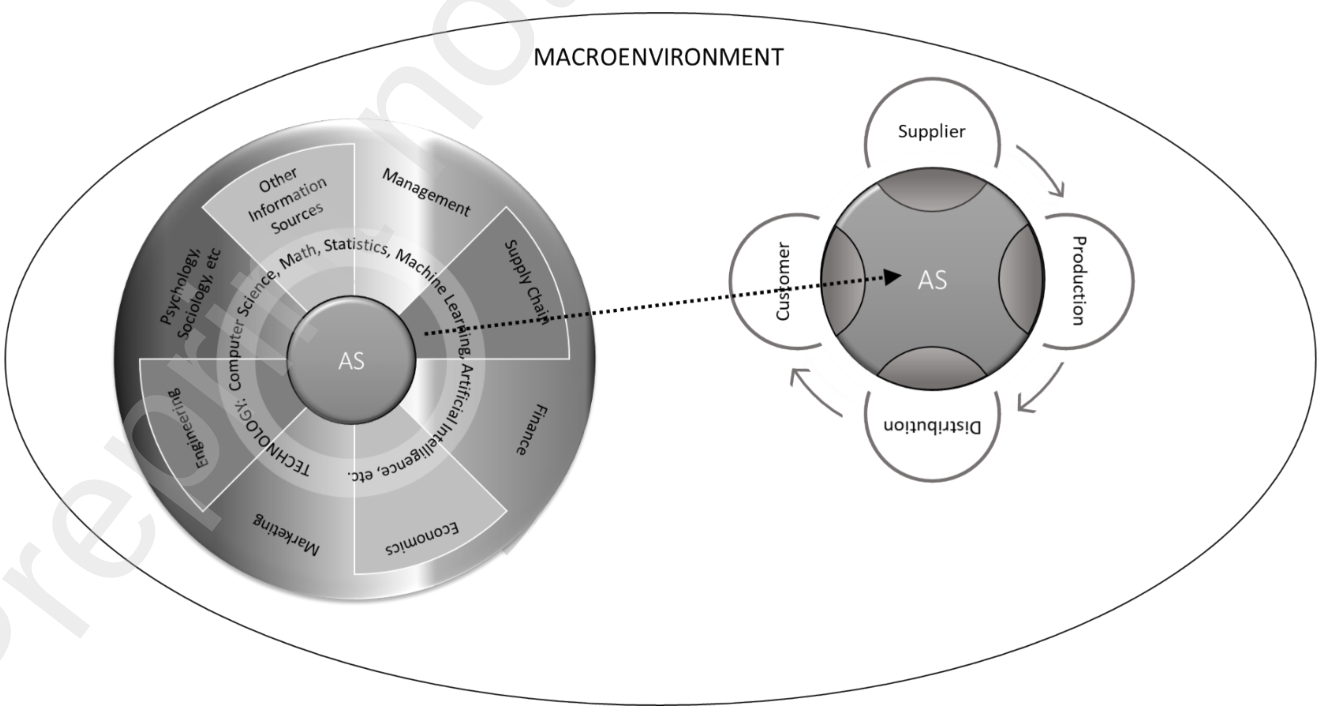

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Figure 1: The Management Accounting Ecosystem (adapted from Akroyd, et al, 2023)

3. Sourcing Data – Organizational Data, Network Data, and Big Data

The data from all functional areas of the company is collected into the Management Accounting System (MAS). From a company's perspective, data has traditionally been categorized as either organizational data or big data. Organizational data originates from within the company, while big data originates from outside the company. This dichotomous view has worked well for a long time, but the proliferation of data using modern technology make it clear that data creation can be viewed as a spectrum. On one end, data creation is completely under the company's control, while the other end has data that is created outside of a company and completely outside of the company's control. However, there is a middle range of data that may be originally sourced from outside of a company but can be manipulated to create more useful information for the company's purposes. Figure 2 depicts this spectrum.

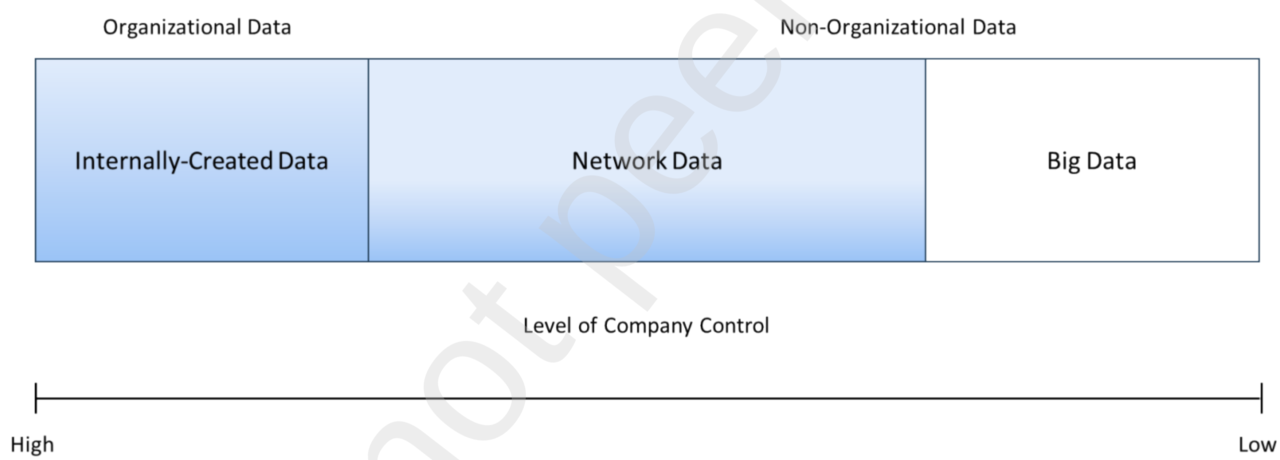

Figure 2: The Data Creation Spectrum

We categorize non-organizational data as either network data (ND) or traditional big data (BD). ***ND*** comes from sources outside of the company, but the company can participate in the data creation process. The supply chain provides intuitive insights for this context. Within the supply chain, this is primarily data coming from supply-chain partners. While a supplier will not share all their information with another company, suppliers can modify their organizational data to become another company's ND. For example, (manufacturing) suppliers can share production capacity, projected lead times, and pricing changes due to input variation. Similarly, customers can share order/demand projections as well as product specifications with other partners in the supply chain. Other examples of ND are data scraped from the web, industry research which a

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company can influence, or information coming from a consulting firm. More types of ND will develop as the amount of data available increases and artificial intelligence helps us categorize it.

BD consists of data that are completely outside of the company's control but may be useful for planning and decision-making. Examples of BD include data on demographic shifts, economic trends, commodity prices, and weather forecasts. BD may also include industry-specific metrics or financial data from other companies in the industry.

Organizational data comes from all areas of the company. The sales, production, warehousing, transportation, marketing, finance, and other departments all have information that is useful to organizational analytics. The "sweet spot" is when management accesses relevant data from multiple sources, applies proper analytics, and uses their own insights to provide actionable intelligence as shown in Figure 3.

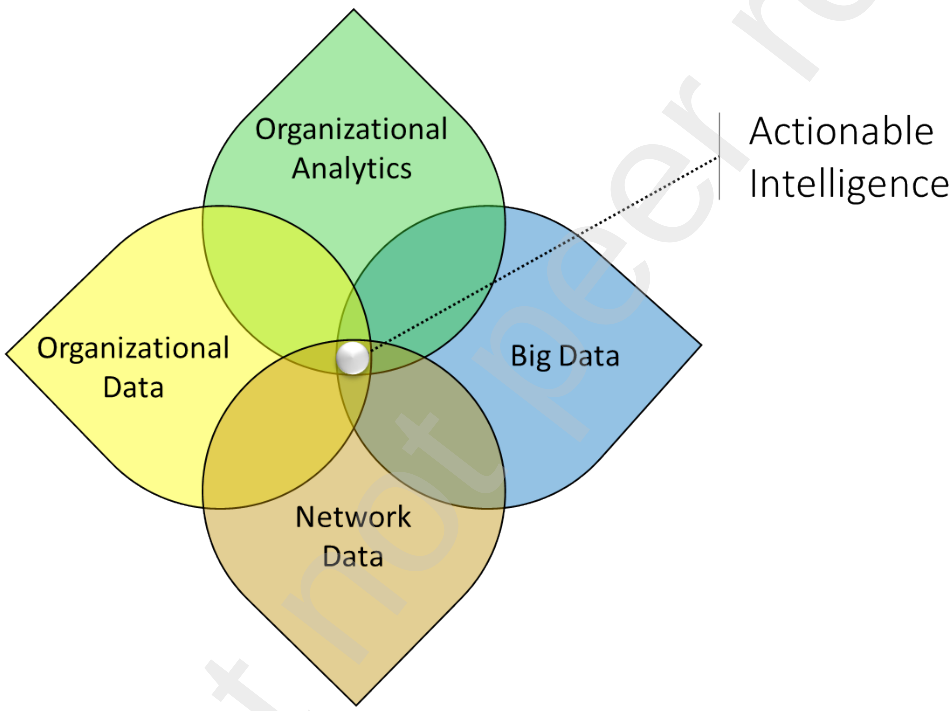

Figure 3: The Intersection of Data and Analytics Creates Intelligence

4. Actionable Intelligence – The Goal of Data Analytics

The end goal of the MAE is to assist management. Figure 4 illustrates information flows between supply-chain partners that lead to actionable intelligence. Data coming from a strategic partner enters a company's internal systems as raw data. The company needs to exercise proper control over the data to validate accuracy and filter out unnecessary information. To turn data into information, managerial accountants use various analytics techniques to move up the DIKAi pyramid. These analytics can answer questions such as those noted in the table below:

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Question by Data Analytic Type	Sample Technique	Data Sources
Descriptive Analytics: What happened?		
How many times did the company stockout during the month?	Counts	Org Data
What is our average lead time by month?	Bar Charts, Histograms	Org Data
What is our error rate by day and shift?	Pivot Tables	Org Data
Diagnostic Analytics: Why did it happen?		
How is weather related to order volume?	Correlation, Regression	Org Data / BD
Is order volume is significantly lower than last month?	Hypothesis testing	Org Data
What is the average freight cost by delivery method?	Pivot Tables	Org Data
Predictive Analytics: What is likely to happen?		
What will be customer demand next year?	Forecasting	Org Data / BD / ND
Which customers are more likely to repurchase a specific product?	Classification	Org Data / BD / ND
Which machines are likely to break down?	Regression	Org Data
Prescriptive Analytics: What action(s) should the company take?		
Which manufacturing plant should the company buy?	Cash flow analysis	Org Data / BD / ND
What is the best shipping route to minimize cost?	Optimization	Org Data / BD / ND
What will our stockout rates be under a new inventory policy?	Sensitivity Analysis	Org Data / ND
Adaptive and Autonomous Analytics: How can the system adapt to changes?		
When should we switch manufacturing lines to new seasonal products?	Machine Learning	Org Data / BD / ND

Table 1: Organizational Problems and Analytics (Adapted from Richardson and Watson (2024))

Information becomes knowledge when it is processed by the Technology Layer within the MAE to better understand and contextualize existing knowledge and experiences. This provides for the creation of new insights, understanding, and perspectives. Various levels of management use this information to support decision-making (typically strategic management), but it is rarely shared in full form with strategic partners. The pinnacle of the DIKAi Pyramid is actionable intelligence. Actionable intelligence can be thought of as cumulative knowledge that

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may assist with future planning and decisions. Actionable intelligence emphasizes the importance of managerial decision-making, and the results of that actionable intelligence can potentially be shared with partners. As shown in Figure 4, once information, knowledge and actionable intelligence are created, they can then be transferred back to the strategic partner.

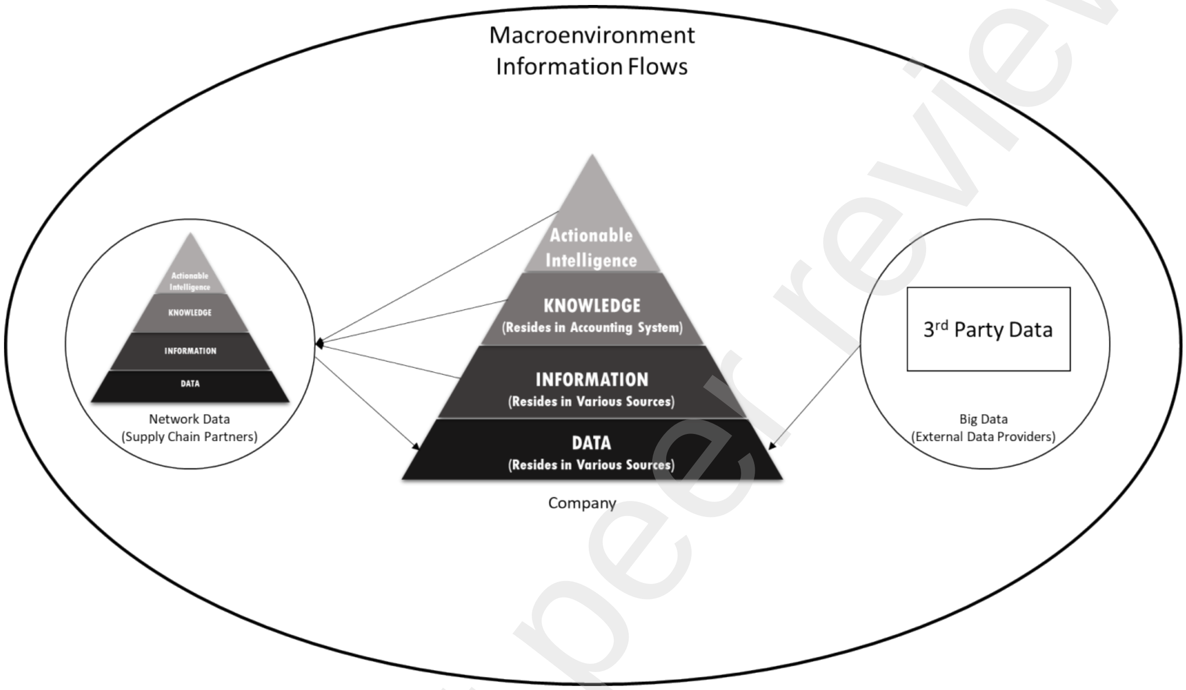

Figure 4: The DIKAi Pyramid and Data Sources

5. Examples of Organizational Data Analytics

This section focuses on analytics techniques that move data up the DIKAi pyramid. Data analytics is typically separated into five types: Descriptive, Diagnostic, Predictive, Prescriptive, and Adaptive and Autonomous. Descriptive and Diagnostic analytics focus on the past, answering the questions: What happened? and Why did it happen?, respectively. Predictive and Prescriptive analytics focus on the future, answering the questions: What is likely to happen? and What actions should the company take?, respectively. Adaptive and Autonomous analytics create a system that can analyze the environment and adapt to change without human intervention, typically incorporating the other analytic types.

As shown in Table 1, a variety of techniques can be used to conduct different types of analytics. Simple tools like Excel can summarize past information for descriptive and diagnostic analytics to answer questions about historical data. Descriptive analytics focus on historical data descriptive statistics, e.g., counts, averages, medians, minimums, and standard deviations. Diagnostic analytics focus on explaining the past by identifying outliers or anomalies using techniques like correlation, regression, summarization, hypothesis testing, and pivot tables.

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More advanced techniques are needed for higher-level analytics. Predictive analytics provides foresight by identifying patterns in historical data and assessing probabilities to help predict future outcomes. Techniques include classification, decision trees, forecasting, and regression. Prescriptive analytics also focuses on the future by performing what-if analysis. It identifies the best course of action given constraints faced by the company (e.g., manufacturing capacity) or changing conditions (e.g., changing interest rates or customer preferences). Techniques include cash flow analysis, goal-seek analysis, optimization, scenario analysis and sensitivity analysis.

Adaptive and Autonomous Analytics combine a variety of information sources to assist decision-making and has the potential for automated decision making with proper training. Adaptive and Autonomous Analytics use historical data and advanced analytical techniques (e.g., artificial intelligence, machine learning, simulations, and survival analysis) to provide rightsight to the company. Rightsight is the ability of the system to continuously determine the right question to ask, the right data to analyze, and the right type of analytical technique so that actionable intelligence can be provided to the right people at the right time in the right format. As with all types of analytics, the appropriate technique depends on the specific question and data used.

6. Harnessing Network Data Through Teamwork

Networks of organizations working near each other, whether physically or united by a goal, provide a unique opportunity for sustainable competitive advantage by leveraging resources that competitors cannot easily access. Unlike traditional business development, the strength of a network lies in its ability to maximize actionable intelligence by operationalizing network data. However, not all networks are equally effective at achieving this potential. The ability to unlock greater actionable intelligence depends heavily on the network's adherence to the principles of social capital – specifically, structural, relational, and cultural embeddedness.

Social capital can be thought of as the aggregate of the resources of a network of institutionalized relationships – which provides members with collectively owned capital. This social capital, jointly owned by all parties in the network, uniquely situates relational embeddedness as the linchpin for transforming raw network data into actionable intelligence with more flexibility in the way it is operationalized than the amount of structural and cultural embeddedness in the system.

Taking supply chains as an example, the structure of these networks is shaped by the nature of interdependence among parties, while the cultural elements – such as shared language, codes, and narratives – develop within the context of ongoing collaboration. While structural and cultural embeddedness can and must be optimized, relational embeddedness requires intentional effort to build and sustain strong relational ties. These ties are defined by trust, shared norms and sanctions, mutual obligations and expectations, and a sense of identification.

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Organizations that recognize the value of investing in social capital are better positioned to benefit from what Sean Covey describes as the “trust dividend.” High-trust relationships increase the speed of results while reducing costs. By fostering trust and developing relationships around shared norms, obligations, and identity, organizations can maximize their social capital, thereby promoting cooperation, facilitating new forms of association, and driving innovation.

Relational embeddedness transforms a loose collection of independent entities into a cohesive, high-performing team. This integration enables the network to approach actionable intelligence with a more nuanced understanding of the sources of available data. From this perspective, actionable intelligence becomes exponentially more valuable when individual units prioritize the network’s collective growth. By centralizing the network and encouraging all parties to share data and invest in mutual success, the network’s potential is fully realized.

7. Conclusion

The MAE provides a comprehensive framework to aid managers in managing and utilizing data for informed decision-making. Managers should integrate this framework to pull data from various sources and utilize the appropriate data analytics techniques. As these basic capabilities spread throughout organizations, they can gain valuable insights into their operations and maximize the output of their resources.

Furthermore, the understanding of data analytics can empower managers to more readily identify the right questions to ask, the right data to collect, and the right techniques to apply. This knowledge enables them to effectively leverage data as a strategic asset, driving success in today's data-driven business landscape. If the knowledge becomes widespread, the company’s success will spread beyond the boundaries of the company itself and empower the entire ecosystem.

Sources and related content

Selected Reading:

To read more about the Management Accounting Ecosystem, see Akroyd, Chris, Kevin E. Dow, Andrea Drake, and Jeffrey Wong. "The New Management Accounting Ecosystem: A Retrospective View and Path to the Future." In *Advances in Management Accounting,* 2023, and Dow, Kevin E., Andrew Fultz, Ned Kock, and Jeffrey Wong. “Towards an integration of strategic management and management accounting.” In *Advances in Management Accounting,* and Forthcoming.

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For greater detail on data analytics and applications in various functional areas see Richardson, V. J., Terrell, K., & Watson, M. W. (2023). *Introduction to Business Analytics*. McGraw Hill.

To gain a deeper understanding of teamwork and forming personal capital we recommend Bourdieu, P. (2018). The forms of capital. In *The sociology of economic life* and Covey, S. M., Covey, S. R., & Merrill, R. R. (2008). *The speed of trust: The one thing that changes everything*. Simon and Schuster.

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