From Descriptive Analytics to Predictive and Prescriptive Analytics:

Navigating the "In-Between Times" of Generative AI

in a Global Solution Services Company

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About the Authors and Dedication

Carlee Diggins

Throughout this program, I have been fortunate to do what I love: helping organizations navigate the human side of change through significant technology transformations. This journey has shown me the importance of the human-AI relationship, highlighting the connection between human hearts and technological efficiency, shaping our future.

I owe immense gratitude to many individuals who have supported me along this path: To Jacob's parents, thank you for your encouragement and support, hosting Terri and me during our working session in MN, and opening doors to opportunities I did not think were possible. Your kindness, support, and generosity have been invaluable.

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Terri Ferinde

I have spent my life engaged in sensemaking and sense-giving, aiding friends and clients in building their capacities to learn and creating more opportunities for youth to thrive. However, it wasn't until I joined the Leadership and Learning in Organizations (LLO) program at Vanderbilt University that I gained the theoretical foundation for my work and passions. I am deeply grateful to the faculty and my exceptional cohort for helping me grow as a scholar-practitioner.

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From Carlee and Terri

Reading this paper, you will see the words “technology,” “AI,” “change management,” and “sensemaking” throughout. However, the moral of the story is teamwork and co-creating together, whether it is human to AI or human to human.

A special thanks to Dr. Eve Rifkin, our advisor and program director, who always keeps it real and is very much a “big deal.” We are grateful for your guidance through the conceptual frame and for shaping complex ideas in elegant ways. Our support team included Kristine Witko, an editing superhero, and Erin Autrey, a design magician.

Our deep appreciation goes to Tom Dick for connecting us to The Company and supporting us along the way. We thank The Company and our project sponsor for granting us the opportunity to explore how to cultivate a culture that embraces generative AI, arguably the most critical organizational opportunity in our lifetime. Lastly, we are grateful to all the technology tools that helped us make sense of our data during this process.

Abstract

Introducing generative artificial intelligence (AI) into organizational processes represents a watershed moment, demanding a fundamental rethinking of processes and culture (Benbya et al., 2020). Traditional change management processes, like ADKAR (Hiatt, 2006), offer research-based tools and strategies to assess readiness for AI adoption but are more effective when adapted and infused with sensemaking to help employees navigate an unknown future state.

In this qualitative study, employees in a global solutions services company (“The Company”) revealed a strong desire and readiness to adopt AI-powered advanced analytics. This desire exceeded employees’ awareness of the change and how it would be applied. Drawing from the literature on change management and sensemaking, interviews, observations, and document analysis from The Company, we recommend adopting an AI-specific change management methodology and strategy focusing on what we call the “AI Change Catalyst Loop,” in which The Company simultaneously focuses on desire, awareness, and knowledge infused with sensemaking. Intentional sensemaking for shared use cases and articulation of the value of advanced analytics will help The Company create a flywheel of momentum to build the ability and skills needed to adopt and utilize advanced analytics successfully.

For The Company, we recommend applying the methodology in three phases. Phase 1 involves establishing an internal change management office focused on data analytics to guide employees through this mindset shift, ensuring continuous learning and leadership alignment. Phase 2 recommends an internal communications strategy emphasizing sensemaking, using narratives and clear messaging to help employees understand their role in the broader organizational goal. Lastly, phase 3 links business success metrics with role-based training to foster continuous improvement and innovation. The new change management approach aims to build a culture of trust, relevancy, and a data-driven decision mindset.

Keywords: data analytics; generative artificial intelligence; change management; ADKAR; sensemaking; antenarratives.

Introduction

Rapid technological advancements have been introduced in the home and workplace today, specifically generative AI (GenAI). This advancement and introduction in employees' homes and workplaces cause intense curiosity and urgency among workers and requires leaders to rapidly guide their teams through uncertainty and unknowns (Poudel, 2019). Introducing GenAI for data analytics into the workplace arguably represents a watershed moment, demanding a fundamental mind shift in organizational cultures (Benbya et al., 2020). When navigating this mind shift, leaders will face complexity, unpredictability, and ambiguity (Bolman & Deal, 2010).

Leveraging data through advanced analytics in an era of ubiquitous information is critical to staying competitive and optimizing people and processes (Roy et al., 2022). As organizations evolve, their transition from descriptive analytics (insights into past events) to AI-powered predictive and prescriptive analytics (forecasting and providing recommendations) marks a significant shift toward proactive and strategic workforce decision-making (Davenport, 2018a). This shift demands technological updates and changes in organizational culture and employee mindsets (Harmat, 2023; Rafferty et al., 2013).

With the rise of GenAI, successful leaders will likely enable adaptive systems that encourage shifts from daily actions to systems approaches with future orientation (Raelin, 2016). As organizations navigate this transformation, change management and sensemaking skills become indispensable (Lüscher et al., 2006). Change management provides methodologies, strategies, and tools to guide teams to readiness through a transition, ensuring that technological advancements like GenAI are integrated smoothly and beneficially (Poudel, 2019). Concurrently, sensemaking brings coherence to mysterious situations, enabling action by developing comprehensive pictures that evolve with data collection, experience, and collaboration (Ancona, 2012). Together, change management and sensemaking empower organizations to manage the change needed with AI adoption and leverage it as an opportunity for innovation and growth.

This study aims to uncover employees' readiness and sensemaking approaches at a large solutions and manufacturing organization, “The Company,”* through an AI-powered transformation. Focusing on change management and sensemaking, this study provides insights and recommendations to navigate the human elements of change through AI transformations to the global industry and its workforce.

*The partner organization requests anonymity. We refer to this organization as “The Company.” All quotes are unattributed, and specific information that may lead to The Company’s identification is generalized.

The Organizational Context

The Company is a global leader providing essential solutions across diverse industries. Operating in more than 170 countries, The Company employs nearly 50,000 individuals and serves over three million customers annually. For more than 100 years, The Company has been a leader in sustainability and innovation.

The Company relies on quality data and strategic analysis to make small and large decisions. With the acquisition of many companies across many industries, The Company has focused on developing an integrated and trusted data platform. As this study started in 2023, leaders shared a tension that The Company needed to strengthen its current data systems and shift mindsets and culture on how data is used across the organization to remain competitive in a marketplace increasingly fueled by AI-powered tools.

The Enterprise Data Office (EDO) focuses on data governance, quality, management, and strategic use of data across the organization. EDO leadership stated their ambition: shifting employee mindsets from relying on descriptive analytics (non-customizable standardized reports that tell what happened in the past) to embracing predictive and prescriptive analytics (dynamic reports that forecast future trends and prescribe strategic actions). Leadership believed this shift will enhance The Company's ability to leverage data to its fullest potential, securing its position at the forefront of its industry in a data-driven world.

While EDO leads data solutions, they closely integrate with Global Business Intelligence (Global BI) and Business Units to understand business issues and provide insights based on data. The complexity of the organizational structure requires strategic coordination, especially in the face of a transformational shift to predictive and prescriptive analytics. See Figure 1 for how teams interact, as seen on an organizational chart.

Figure 1

Cross-Functional Teams Interaction

Note. From an employee of The Company, personal communication, March 4, 2024. Copyright 2024 by The Company.

The Company's expertise in its field is a product of its innovative solutions and people. The workforce, strong in experience, diversity, and expertise, is the backbone of its operations and innovation, which embody its values. However, as The Company stands at the beginning of a new analytical era, the project sponsors, our project team's primary contact points, and company leaders acknowledge that adopting advanced analytics is slow and challenging. Leadership shared that they recognize that the journey from advanced analytics awareness to fluency is a critical strategic pivot, which calls for an intentional shift in mindset. One of the project sponsors stated:

> *So, there's a journey we probably need to lay out for them, just so they can understand in a non-technical way, because that's where we're losing. They [see] AI, and it's all over the place. That's why we split it up with descriptive—reporting the news—[then] predictive—reporting where the news could be—and then prescriptive is changing the news.*

The Company recognizes the need to focus on data literacy as a first step in moving to advanced analytics. The EDO annually hosts an annual "Enterprise Technology Solutions Data Fest." This spring event is an open house to deepen data awareness, foster an appreciation for data, and better understand how data drives The Company and contributes to customers' success. Data Fest features booths and speakers focused on discovering, trusting, and using data. During our study, The Company launched a "Data Community of Practice," which aims to provide communications, training, "lunch and learn" sessions, and spotlight interviews with leaders. The Company's leadership envisions cultivating a data-centric culture—where every employee understands and embraces predictive and prescriptive analytics.

Problem of Practice and Project Questions

With the industry's ambition in a data-driven world, The Company plans to implement predictive and prescriptive analytics to enhance strategic decision-making and innovation. This shift requires technology updates integrating AI, a fundamental organizational culture change, and employee mindsets shifting toward advanced data usage. This study focused on the shift of employee mindsets to embrace advanced analytics that anticipate future trends and prescribe strategic actions. The Company is in the early stages of this transformation and needs to understand the readiness of its employees for this mindset shift and gain insights into how to manage the change.

This study explored how The Company can effectively manage this significant mindset shift, focusing on the roles of change management and sensemaking as they transition to advanced analytics. The outcome aims to provide actionable insights into The Company's current transformation and inform broader practices of AI adoption in the industry.

Project Questions

The project investigated the following questions:

Q1: How is The Company poised to manage change regarding adopting and utilizing advanced analytics?

Q2: In what ways does an intentional focus on sensemaking help The Company speed the adoption of new technology?

Research Synthesis

Introduction

Across industries, individuals constantly seek to predict what will happen next. The deep-rooted need to predict helps humans gain control of their environment, reduce uncertainty, and make decisions that optimize outcomes (Gilbert & Wilson, 2009). The ability to predict incites awe and fear (Silver, 2020) depending on how one perceives what is known and unknown about the future. In 2024, just a year after American tech giant Bill Gates declared that the “Age of AI has begun” (Gates, 2023), businesses worldwide are grappling with the potential for AI to facilitate prediction more easily and fundamentally change how business operates.

Just as the world of commerce shifted when electricity became widespread or the Internet became accessible on a desktop, industries today now exist in what may be described as the “in-between times” (Agrawal et al., 2022) when the power of AI to facilitate prediction seems possible but just out of reach. AI is now commonplace in predicting what products we might want to buy on Amazon or suggesting connections on LinkedIn. In the workplace, a global survey from McKinsey & Company (2023) reported that most employees have some exposure to generative AI, and nearly a quarter of American workers—mainly in the tech sector—use AI regularly in their work. Increasingly, workers across industries are seeing how AI can lead to shifts in their work by automating tasks and saving 60-70% of their time (McKinsey & Company, 2023). While workers are increasingly adopting AI to enhance productivity, leveraging AI systemically to directly reduce operational costs or generate new revenue in core businesses presents additional challenges, including the need for strategic application of AI, investment in worker support and training, and the broader economic context (McKinsey & Company, 2023). Harnessing generative AI for specific purposes depends on good data, good judgment (Bedué & Fritzsche, 2022; Dwivedi et al., 2023; McKinsey & Company, 2023), and developing a systems mindset to understand how AI might facilitate prediction in context (Agrawal et al., 2022; Kissinger et al., 2021).

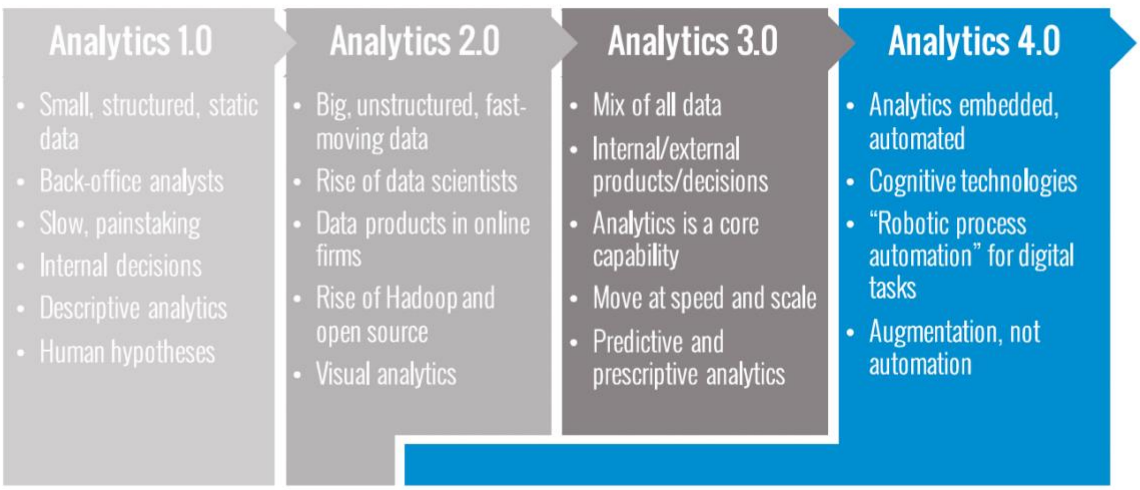
Prediction is possible with advanced analytics. Advancing to the next era for business analysis and decision-making will require a mix of strategy, technology, investment, and leadership. Change management processes will be essential to scale and spread the promise of advanced analytics (Davenport, 2018a). Moreover, the complexity of this specific change will require sophisticated sensemaking at every stage of the process (Steigenberger, 2015). To support this inquiry for The Company, the literature review delved into three key areas: change management, sensemaking, and technology adoption specific to AI in data analytics. The review explored which change management process might best support The Company and how sensemaking might contribute to success in advanced analytics adoption with AI.

Using Generative AI for Strategy and Data Analysis

Today's leaders will need a strong foundation in analytics, with trusted data and a data-forward culture, to navigate this new epoch of AI (Davenport, 2018a). Imagining a future where AI adds new knowledge beyond human reason (Kissinger et al., 2021) requires collective understanding and readiness. Companies need to build data competencies and then be ready for the Analytics 4.0 era, where they go "all in" to radically transform their products, processes, strategies, customer relationships, and cultures (Davenport, 2013, 2018a, 2018b; Davenport & Mittal, 2023). Moving to the era of Analytics 4.0 requires close assessment and shoring up culture, analytics capabilities, data and technology capabilities, and individual capabilities (Davenport, 2018a). Davenport (2018a) conceptualized a "leading tail" where organizations mainly experiment with advanced analytics while shoring up data platforms and building expertise. Figure 2 illustrates the evolution of business analytics ranging from a less mature program to one operational with GenAI.

Figure 2

Evolution of Business Analytics



Note. From "From Analytics to Artificial Intelligence," by T. H. Davenport, 2018a, *Journal of Business Analytics, 1*(2), p. 74 (https://doi.org/10.1080/2573234X.2018.1543535). Copyright 2018 by Taylor & Francis Journals.

In the root cause analysis for this study, leaders in The Company described the demand to be competitive by shifting from reliance on descriptive analytics to embracing predictive and prescriptive analytics to leverage data to predict the future better, increase efficiencies, and improve outcomes. The transition to advanced analytics represents a shift in how organizations leverage data to inform strategic decision-making and promote new mindsets for systems thinking.

In their 2022 book, *Power and Prediction*, Agrawal and co-authors outlined three approaches to adopting technology. Point solutions address specific, well-defined problems within an existing system. They are often the first step in technological adoption, providing immediate benefits without requiring significant changes to the current system. Depending on the users' interpretations, an HR chatbot serves as a point solution in technology adoption by facilitating operations and acting as a self-service system or an HR assistant (Harmat, 2023). Application solutions, on the other hand, target specific related problems or processes. They may necessitate changes to the system but are confined to improving specific functions within the organization. An example might be digital health records that connect related processes around tracking a patient’s health and may or may not connect to billing, thus improving how existing systems work together (Agrawal et al., 2022). Ultimately, systems solutions involve entirely rethinking and redesigning existing systems to integrate and fully leverage the new technology. In a global company with multiple delivery points, a systems solution would reimagine how goods and services are delivered to each customer across many product lines and predict what the customer might buy in the future. For a multinational business-to-business corporation, the leap to systems solutions requires awareness, understanding, trust, imagination, and a collective change in mindset (Beer & Nohria, 2000; Kotter, 1996).

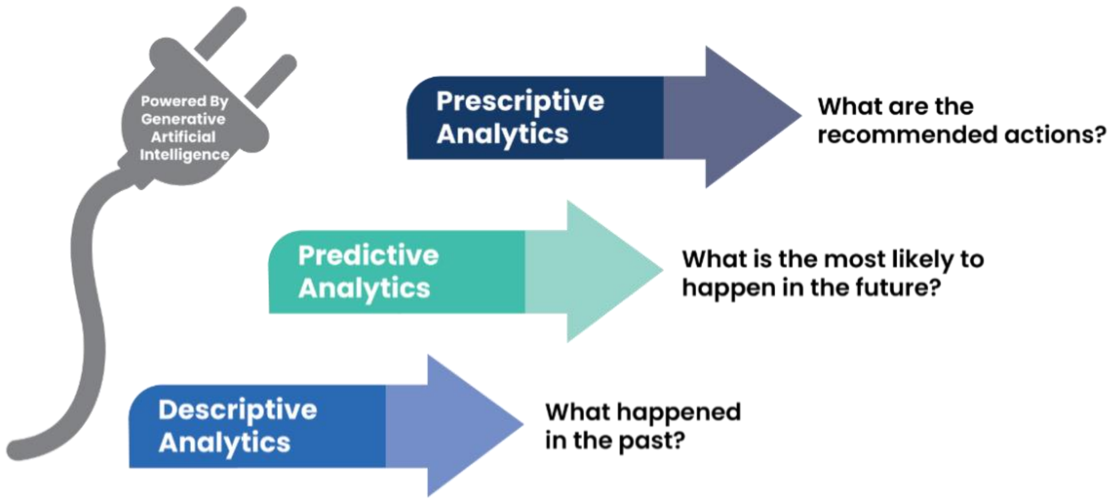
Understanding Analytics

Analytics is the science of applying statistics and other quantitative methods and technology to large amounts of data to obtain insights and strengthen decision-making (Davenport, 2018a; Roy et al., 2022). It is a multidisciplinary approach that combines machine learning, operations research, and data-driven methods to analyze data, predict future trends, and prescribe actionable decisions to optimize outcomes (Bertsimas & Kallus, 2020). Analytics involves the use of statistical, computational, and mathematical methods to derive insights from data, which can then inform decision-making processes, particularly under conditions of uncertainty (Bertsimas & Kallus, 2020; Davenport, 2018a; Mortenson et al., 2015; Roy et al., 2022).

There are three types of analytics in today's business environment. Descriptive analytics focuses on what has happened in the past and is used widely throughout organizations, serving as a foundation for advanced analytics (Davenport, 2018a). Predictive analytics then tells us what will likely happen in the future based on the data (Roy et al., 2022). Prescriptive analytics takes the process further, recommending how to act in real time and showing potential outcomes for decisions (Roy et al., 2022). Utilizing this range of analytics requires skills and a mindset that enables organizations to leverage organizational learning and thrive by making decisions rooted in data analysis (Davenport, 2018a; Roy et al., 2022). With the explosion of AI and the push to predictive and prescriptive analytics, fluency about these terms and the opportunities and challenges of these tools extends beyond operations employees and data scientists to encompass a broader range of positions within the organization (Jöhnk et al., 2021). Furthermore, adopting predictive and prescriptive analytics significantly increases employee productivity, optimizes efficiency, and elevates overall performance (Wijayati et al., 2022). Figure 3 describes the different descriptive, predictive, and prescriptive analytics considerations.

Figure 3

Descriptive, Predictive, and Prescriptive Analytics



Key findings from the literature underscore the necessity of a structured change management strategy for organizations to facilitate the transition to predictive analytics (Davenport, 2018a). The need for an effective change management strategy is profound, suggesting that a successful transition and change relies on the technological infrastructure and a culture receptive to advanced analytics, comprehensive training programs, transparent communications, and leaders that are change champions for the vision (Kanitz et al., 2023; Phillips & Klein, 2023). Organizations effectively managing this shift can expect benefits in efficiency, productivity, risk management, innovation, and problem-solving, positioning themselves at the forefront of the AI-driven evolution (Jöhnk et al., 2021; McKinsey & Company, 2023; Wijayati et al., 2022).

Change Management: Identifying a Theoretical Framework

Shifting from descriptive to predictive and prescriptive analytics requires new approaches and mindsets. A change management framework can guide The Company through a research-based process to lead the people side of change (Galli, 2018). As the organization transitions from a current state to a desired future state, leaders, project teams, and individuals must recognize the need for change and implement strategies to evolve (Phillips & Klein, 2023). Given widespread fears of how artificial intelligence will replace jobs and change the nature of the workforce, change management strategies that put people first are essential. While tempting to emphasize Theory E (Economic, often top-down-driven focus on value) and how predictive analytics will increase efficiencies, the combination with Theory O (Organizational Capability, with strong stakeholder engagement) is needed to simultaneously enhance shareholder value and build a strong corporate culture (Beer & Nohria, 2000).

Selecting and adopting a change management model depends on corporate culture, historical experience with given models, and leadership preferences. Given the potential enormity of the shift to predictive analytics, a fresh examination of the potential models provides new insights relevant to this specific change management need. Research-based and tested change management models provide a starting point for potential approaches for corporate adoption of predictive and prescriptive analytics in strategy decisions. Models frequently follow a three- to five-step approach with varying names, generally focused on 1) identifying the needed change; 2) gathering data and knowledge; 3) designing and explaining the approach; 4) implementing the change; and 5) monitoring and refining the approach (Galli, 2018). Table 1 provides an overview of proven strategies with potential applicability.

Table 1

Change Management Models in Order of Introduction

Model	Strength	Basic Stages
Lewin's Change Management Model (Lewin, 1951)	Simplicity. A gradual approach breaks the change process into manageable steps.	Unfreezing Changing Refreezing
McKinsey 7-S Model (Waterman, 1982)	A comprehensive, balanced view of organizations with emphasis on hard and soft elements and recognition of the interconnectedness of organizational components.	1. Strategy 2. Structure 3. Systems 4. Skills 5. Staff 6. Style 7. Shared goals
Bridges' Transition Model (Bridges, 1986)	A comprehensive, human-centered approach to change.	Ending, losing, and letting go The neutral zone The new beginning
Kotter's 8-Step Change Model (Kotter, 1996)	Clear steps that engage employees throughout the process. Requires strong and focused leadership.	1. Create a sense of urgency. 2. Create a core coalition. 3. Develop and form a strategic vision. 4. Communicate and share vision plans. 5. Empower employees to act on the vision. 6. Generate short-term wins. 7. Consolidate gains and produce more change. 8. Initiate and set new changes.
Six Sigma (Harry & Schroeder, 2000)	Data-driven, structured approach to process improvement.	DMAIC: • Define • Measure • Analyze • Improve • Control
ADKAR Model (Hiatt, 2006)	Supports managing the people side of change.	Stages or goals: 1. Awareness

		2. Desire 3. Knowledge 4. Ability 5. Reinforcement
Switch Change Management (Heath & Heath, 2010)	Clear and practical approach with an easy-to-understand metaphor that garners buy-in.	Direct the rider Motivate the elephant Shape the path

Evaluating Change Management Approaches for Adopting Advanced Analytics

To support The Company's desired embrace of advanced analytics, we sought a change management model that is simple enough to grasp quickly, emphasizes the people side of change, including leadership and culture imperatives, and is sophisticated enough to embrace the complexities of a technological transformation. Lewin's Change Management Model is known for its simplicity and effectiveness, breaking the change process into three digestible stages: unfreezing, changing, and refreezing (Cummings et al., 2016; Lewin, 1951). The ADKAR change management model is also easy to grasp, spelling out a linear framework designed to guide individuals and organizations through the process of change at a personal and professional level (Hiatt, 2006). Also simple in its metaphor approach is the Switch Change Management model that emphasizes securing buy-in across all levels of an organization while explaining how to direct the rider and motivate the elephant to adopt change (Heath & Heath, 2010).

Seeking a people-forward change management approach, we sought a framework that allowed the exploration of individual readiness and adoption. Bridges' Transition Model excels at handling employees' psychological transitions, which is potentially vital in shifting to a data-centric culture. Its focus on beginnings, transitions, and endings aligns well with the iterative nature of analytics projects (Bridges, 1986). However, the model may not provide enough structure for the technical aspects of implementing analytics solutions, requiring additional frameworks to address these needs. The ADKAR model emphasizes that successful change is rooted in facilitating change one person at a time, acknowledging that organizational change is the cumulative result of individual changes (Jones-Schenk, 2019). The model structures around five sequential and cumulative milestones or outcomes that an individual must achieve for change to be successfully realized (Hiatt, 2006). Offering possibilities, the Lewin model's core assumption is that employees need time to reflect, adapt, and incorporate new changes (Galli, 2018).

Understanding that the shift to advanced analytics is a leap in mindsets, processes, and organizational culture, we sought a robust change management process. Kotter's 8-Step Change Model provides a detailed roadmap for change, encouraging broad-based employee engagement and strong leadership (Kotter, 1996). Its stepwise approach is beneficial for aligning large teams toward incorporating analytics into decision-making processes. The emphasis on creating short-term wins, building on the change, and anchoring the changes in corporate culture (Galli, 2018) might be beneficial in this scenario. McKinsey 7-S Model's holistic view of organizations ensures that all critical elements, including skills and staff, are aligned, which is essential for successfully integrating analytics systems. However, its broad focus might dilute attention from specific analytics needs, such as data governance or the development of predictive models, without supplementary, more focused change strategies (Galli, 2018). Six Sigma offers a rigorous, data-driven approach that complements the adoption of analytics well, focusing on defining, measuring, analyzing, improving, and controlling business processes (Harry & Schroeder, 2000). However, the highly structured nature of Six Sigma can be rigid, potentially stifling innovation and adaptation in fast-evolving fields like analytics (Galli, 2018).

In a thorough review of the change management literature, we sought a frame that would fit The Company's context and speak to the key leaders we were engaging. We thought the Kotter model could be highly relevant in adopting AI in a business setting with an emphasis on creating a sense of urgency for the change (Kotter, 1996). While the Kotter model may adapt quickly to the dynamic change needed to shift mindsets toward predictive analytics, the sequential steps may delay the rapid adaptation needed in fast-paced analytics projects. The Lewin and Switch models seemed too simplistic for the complexity of the change. The McKinsey 7-S and Six Sigma models offered more robust solutions but seemed to expand the scope of what was possible to study for the project's purpose.

After careful consideration and thorough review of multiple models, we chose the ADKAR model for the blend of simplicity and sophistication. The clear structure—awareness, desire, knowledge, ability, and reinforcement—makes intuitive sense to people. Since its release by John Hiatt in 2006, the spread of the ADKAR model has been supported by the Prosci organization (https://www.prosci.com/) and is well-known in business schools, providing common language and baseline knowledge among industry leaders. Despite its simplicity, the ADKAR model covers all essential dimensions, creating a holistic approach to managing change. The steps provide a diagnostic tool to identify gaps in the change process. Organizations can pinpoint specific areas that need improvement by evaluating each milestone, making the change process more targeted and effective (Holt et al., 2007). Finally, the ADKAR model emphasizes individual change and ensures that the emotional and psychological needs of employees are addressed, which is crucial for successful change implementation (Weick et al., 2005) and potentially the upskilling and reskilling of the workforce needed for advanced analytics (Jöhnk et al., 2021). Ultimately, the ADKAR model is flexible and can be adapted to other known or proprietary change management models The Company may use, contributing to the project's relevancy and usefulness.

Making Sense of Sensemaking

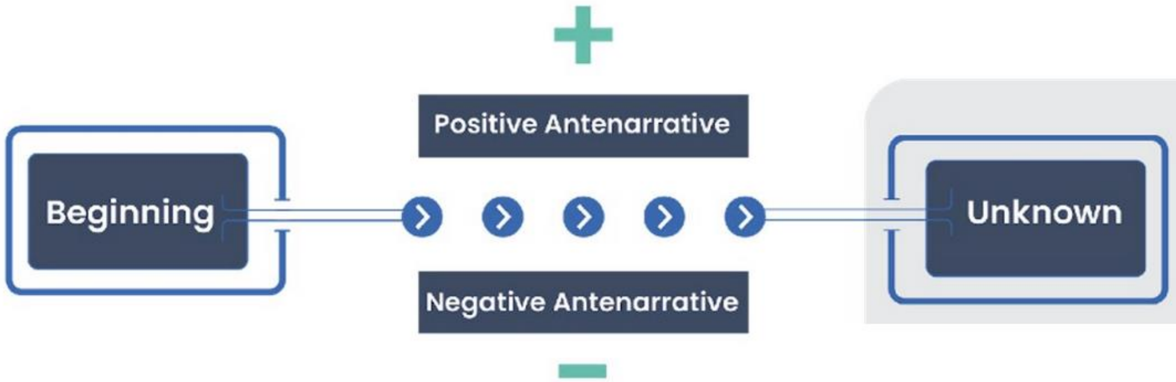
One of the limitations of the ADKAR model is that while the model outlines the phases individuals go through, it does not provide detailed instructions for leaders on how to facilitate these transitions effectively (Galli, 2018). We dove into the sensemaking literature to deepen the ADKAR conceptual frame and provide The Company with strategies to become a sensemaking organization.

Sensemaking is essential to change management because it involves interpreting and creating order, particularly during organizational change (Lüscher et al., 2006). Sensemaking helps individuals and groups understand and interpret the changes around them, enabling them to respond effectively and adapt to new technologies (Maitlis & Sonenshein, 2010). Initially conceived by Weick (1995), sensemaking theory describes how individuals and organizations interpret and give meaning to their experiences, particularly in ambiguous, unexpected, or confusing situations. According to Weick, sensemaking is a process triggered by events that disrupt an individual's or group's expected reality, prompting them to seek explanations that restore continuity and rationalize their experiences (Harmat, 2023). The theory emphasizes that sensemaking is retrospective, as individuals look back on events to understand them, but it can also be prospective, shaping future actions and interpretations (Maitlis & Sonenshein, 2010).

A subsequent interpretation of sensemaking by Boje (2001) leans into the prospective possibilities in conceptualizing “antenarratives.” An antenarrative is a form of narrative that is not yet fully formed or is in the process of taking shape. Boje (2011) described antenarratives as emergent, fragmented, and polyphonic. These qualities enable antenarratives to link lived experiences with fully developed narratives. When trying to predict or increase comfort with the possibilities of prediction, the concept of antenarrative is helpful in the context of organizational change and the adoption of AI-based solutions. In a study of a large financial organization aiming to become a digital leader, Poudel (2019) offered that antenarratives help managers and practitioners make sense of the ambiguous and uncertain landscape that AI technology presents. He posited that antenarratives could categorize themselves into positive and negative themes, influencing how strategy practitioners perceive and respond to the introduction of AI (Poudel, 2019). Figure 4 illustrates Poudel’s framework.

Figure 4

Poudel's (2019) Antenarrative Theoretical Framework



Note. From "Making Sense or Betting on the Future?: Identifying Antenarratives of AI Projects in a Large Financial Organization," by D. Poudel, 2019, *Electronic Journal of Business Ethics and Organization Studies, 2*(2), p. 24 (http://ejbo.jyu.fi/pdf/ejbo_vol24_no2_pages_20-33.pdf). Copyright 2019 by the Business and Organization Ethics Network.

Positive antenarratives, such as normalized change and anticipated benefits, promote strategy practices by framing AI adoption as a necessary response to an ever-changing business landscape and emphasizing AI's potential benefits to the organization. These narratives help practitioners overlook uncertainties and focus on the competitive advantages that AI projects may offer. On the other hand, negative antenarratives can impede strategy practices by highlighting the risks and uncertainties associated with AI, potentially leading to resistance or skepticism toward change (Poudel, 2019). Encouraging positive antenarratives and addressing negative antenarratives provides promise for accelerating technology adoption in a change management framework.

Adopting generative AI in advanced analytics is not a typical technology adoption process. The nature of technology requires advanced conceptualization at all levels of the organization. Prospective sensemaking—the forward-looking process where individuals or groups within an organization anticipate and make sense of future events, changes, or uncertainties—can help create mental models or narratives about what might happen and how to respond to those potential future scenarios. This type of sensemaking is beneficial when organizations face significant changes or unknowns (Boje, 2001; Boje, 2011).

When prospective sensemaking integrates with a people-forward change management process, it can help the leap into embracing predictive and prescriptive analytics. The literature shows that such an approach will increase understanding of change and employee buy-in. Leaders can ensure that multiple perspectives are considered by involving others in the sensemaking process, leading to a more comprehensive understanding of the change and its implications for different parts of the organization (Ancona, 2012). Sensemaking supports adaptability to help organizations remain agile and responsive to new information and changing circumstances, which is crucial in dynamic business environments (Steigenberger, 2015). Sensemaking can facilitate better communication by helping leaders articulate the reasons for change in a way that resonates with employees, thus aligning their perceptions and expectations with the organization's goals (Maitlis & Sonenshein, 2010).

Integrating the concept of sensemaking from Weick et al. (2005), antenarratives can be seen as tools that facilitate the sensemaking process during organizational change. Sensemaking involves turning circumstances into comprehensible situations that prompt action, and antenarratives contribute to this by offering preliminary, adaptable stories that can evolve as situations change. This adaptability is crucial in managing organizational change, where new information and contexts can shift the direction of planned changes. In practice, using antenarratives in change management involves encouraging the creation and sharing of these stories among stakeholders to explore different perspectives and potential outcomes. This process not only aids in sensemaking but also in sensegiving, where leaders and managers help others in the organization to understand and engage with the change process. By fostering a narrative environment, organizations can better manage the uncertainties and complexities associated with change, leading to more effective and coherent organizational actions. In summary, antenarratives serve as a vital component in the toolkit for change management by providing a flexible, inclusive, and dynamic approach to understanding and navigating change within organizations.

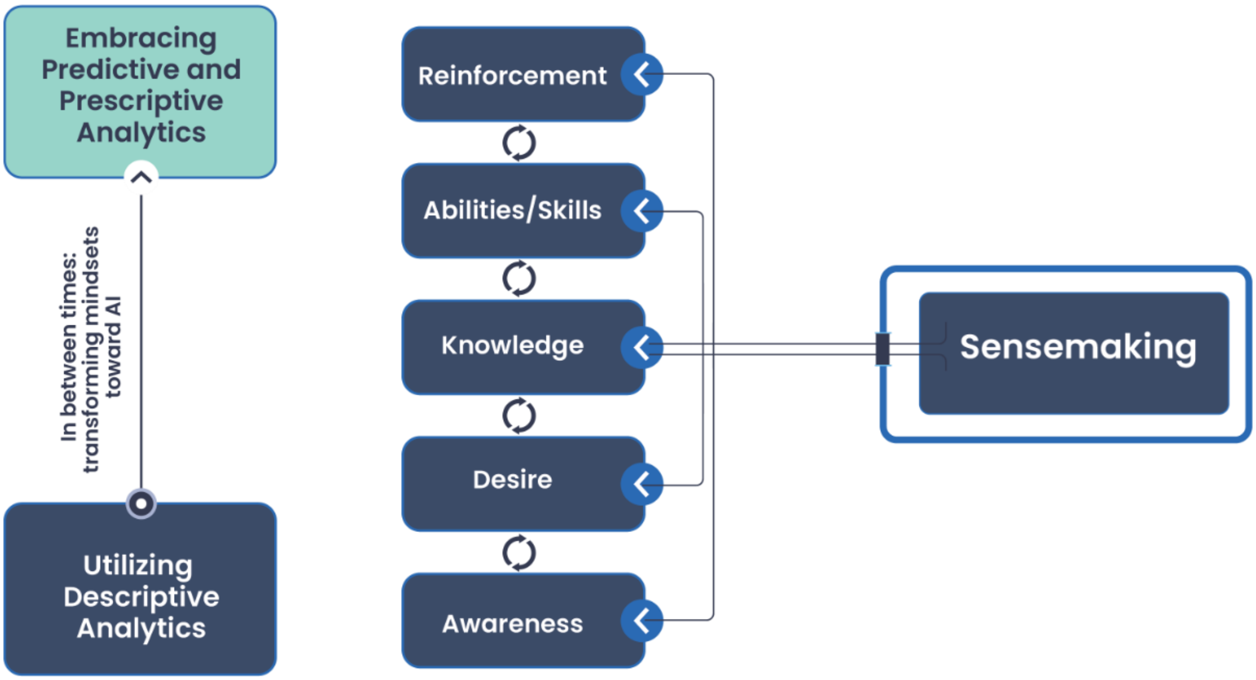
Conceptual Framework and Project Questions

Conceptual Framework: From Descriptive to Predictive Analytics

The leap from utilizing descriptive analytics in daily operations to embracing predictive and prescriptive analytics requires a thoughtful and deliberate change management approach infused with sensemaking. Our conceptual framework accepts the uncertainty of the "in-between times" (Agrawal et al., 2022) as generative AI spreads rapidly in industry, testing the ability of organizations to change quickly. This leap may require extensive sensemaking to change practice and comprehend the enormity of a technology that can change all elements of society (Davenport & Mittal, 2023). With its focus on how individual people experience change, we identified ADKAR as the change management model (Hiatt, 2006) and considered how sensemaking might be embedded throughout the process. Prospective sensemaking with antenarratives (Boje, 2011; Poudel, 2019), representing dynamic and evolving stories, was examined as essential for understanding how change is negotiated throughout all stages of the change management process (see Figure 5).

Figure 5

Conceptual Framework of an AI-Fueled Analytics Shift with a Change Management Process



Data Collection and Project Design

Introduction

The project was designed to examine the readiness for change within The Company and the positive and negative narratives from leaders. The goal is to provide recommendations to guide employees' mindsets from relying on descriptive analytics to adopting AI-powered advanced analytics. The ADKAR curve and the antenarrative theoretical framework were the tools we utilized for the project design.

The project was structured to answer our two project questions. First, we aimed to identify how The Company is poised to manage the change by exploring employees' readiness. Second, we examined how an intentional focus on sensemaking by leadership can foster a mindset shift among employees, leading The Company toward a future where data-centric decision-making is standard practice. The data collection approach consisted of two primary methodologies: 1) interviews with selected organizational leaders and end-users, and 2) observational fieldnotes and document analysis at The Company's annual Data Fest. The interviews with leaders and end-users were designed to capture current experiences, perceptions, and attitudes toward change. The observations and the document analysis from Data Fest aimed to capture the current culture of The Company through different observations of stories, symbols, and sensemaking. These methods were designed to understand the current state and provide recommendations for The Company, emphasizing the qualitative data that quantitative data alone could not reveal. Table 2 illustrates a high-level overview of the methods used.

Table 2

Data Collection Methods

Method	Audience	Approach
Interviews	Leaders End users Project sponsors	21 interviews total -8 end users -13 leaders
Observations	Various levels	-Observations at Annual Data Fest -Document analysis of display materials

The project design was co-created between the project team and the project sponsors. These sponsors served as the primary points of contact for The Company and provided insights and direction throughout the process. The sponsors played a role in selecting interview participants, scheduling interviews, helping create interview questions, and inviting us to the Annual Data Fest. Their understanding of the organizational culture and strategic vision from a leadership perspective helped refine the statement of work and project focus. The following sections elaborate on the interviews, observations, and document analysis, including limitations.

Interviews

Purpose

The interviews were designed to gain insights that are aligned with the project's conceptual framework of change management and sensemaking, utilizing the ADKAR model as our tool and antenarrative use. The interviews explored employees' experiences with data analytics and their readiness to adopt predictive and prescriptive analytics.

Participant Selection

The project sponsors selected the interview participants, classifying participants as leaders or end users. The selection process included those leading the change (leaders) and those impacted by it (end users). Initially, 23 interviews were scheduled for interviews, nine with end users and 14 with leaders. The project sponsors added calendar invites with a Microsoft Teams link to each calendar invite, but two participants did not attend. However, the 21 interviews provided enough perspectives for our findings and recommendations. See Appendix A for a list of the interview schedule.

Participants were strategically chosen from key departments—Enterprise Architecture and Enterprise Data Organization, Global Business Intelligence, International Markets, and Finance Planning and Analysis—ensuring a comprehensive understanding of analytics usage across The Company. This representation from multiple departments was crucial to capturing the overall view of the culture and The Company's readiness for change.

Interview Protocol

The interview protocol included change readiness and sensemaking, aligning with the project's conceptual framework. The protocol utilized the ADKAR model and antenarratives as the tools to create interview questions (see Appendix B for the full interview protocol). The project team utilized a semi-structured interview approach and a customized replication structure, guided by Ravitch and Carl (2019), allowing for conversation flexibility and encouraging descriptive narratives. This approach used the same vital questions but customized each conversation through individualized specifics.

Interviews were conducted on Microsoft Teams for 30 minutes. Each session was facilitated by one of the project team members and began with an introduction of participants, an overview of the interview purpose, and a confidentiality statement, highlighting that any shared analysis would be anonymized. We were prepared to describe descriptive, predictive, and prescriptive analytics with a pre-made graphic but found that most participants had shared language. We used the phrase “advanced” analytics throughout the interviews when discussing predictive and prescriptive analytics. Interviews were recorded by Fathom and Otter.ai by the project team and recorded through Microsoft Teams by The Company. The project team utilized Fathom and Otter.ai transcripts for the data analysis.

Embracing a Participatory Action Research approach (Ravitch & Carl, 2019), the questions were co-created between the project sponsors and the project team, ensuring the questions aligned with the project's scope conceptual framework and matched The Company's culture. The interview protocol consisted of two sets of questions tailored to either leaders or end-users, and each set had question categories of 1) change management, 2) sensemaking, and 3) investment in learning. The questions focused on experience, behavior, opinions, values, feelings, and knowledge.

For the change management phase, questions were formulated to assess The Company’s readiness along each stage of the ADKAR model: awareness, desire, knowledge, ability, and reinforcement. Participants were asked to rank their own, if they were an end user, or their teams’ engagement, if they were a leader, with each stage. The questions for this included:

Please answer the degree to which your team:

1. Is aware of the potential to utilize advanced analytics.
2. Desires to adopt and explore advanced analytics.
3. Has the knowledge to apply and utilize advanced analytics.
4. Has the skills and abilities they need to use advanced analytics.
5. Regularly uses advanced analytics to measure impact.

Additional questions were asked, such as, "Can you identify specific areas of your daily tasks that could benefit from advanced data analytics?" and, "Do you make a distinction between descriptive and predictive analytics in your work?" to learn more about interviewees' placement on the ADKAR curve and their readiness for change.

The questions on sensemaking uncovered the stories and narratives surrounding using advanced analytics. Leaders were asked about their strategies for promoting data literacy within their teams, while end users were encouraged to share their perceptions of such efforts by their leaders. Questions identified positive and negative antinarratives within these answers. A few examples include:

- "What kinds of stories or conversations do people tell about using advanced analytics?"
- "Can you walk us through how new technologies have typically been introduced and used within your team?"

Lastly, the investment in the learning phase sought to identify barriers to learning advanced data analytics and determine the most effective formats and time commitment for enhancing data analytics capabilities.

Appendix B contains the full interview protocol, with a detailed outline of specific questions during each phase.

Observational Fieldnotes

Purpose

The observational field notes of the project aimed to complement the insights from the interviews by capturing authentic employee reactions and the culture at The Company's third Annual Data Fest. The real-time observation validated information gathered from the interviews (Ravitch & Carl, 2019). These observations were critical in revealing sensemaking processes, particularly the antenarratives that leaders and end users construct around the transition to advanced analytics.

Site Selection

The site for observation was The Company's Annual Data Fest, an event that congregates a diverse representation of the organization's workforce. This event was chosen as the observation site because it provided a dynamic setting where leaders set the tone for the future state of a data-driven organization, and employees' behaviors and dialogues around analytics naturally manifest within an unstructured setting. The event was held at The Company's headquarters and hosted over 900 attendees. There was a post-event event happy hour for everyone involved in organizing the event, from booth hosts to event coordinators to the Chief Information Officer (CIO).

Observational Fieldnotes Protocol

The observational fieldnotes protocol during The Company's Data Fest was designed to function as a data collection method in the data triangulation to bolster the validity of the findings. Utilizing Ravitch and Carl's (2019) suggestion, the role of the project team members at the event was participatory and fully engaged as observers and participants. This dual role was essential for capturing authentic experiences and understanding the ongoing sensemaking process. As active participants, we attended the keynotes, engaged in discussions at each booth, interacted with attendees, and attended the post-event happy hour.

Continuing to draw on the advice of Ravitch and Carl (2019), careful consideration was given to what was documented in the field notes, paying particular attention to interactions suggesting antenarratives and prospective sensemaking. Decisions on how to write down observations were guided by the project's conceptual frame and emerging themes from the interviews that were done pre-event. The timing of notetaking was also strategic; observations were recorded promptly via voice memos or writing, and keynotes were recorded using Otter.ai.

We understood that any printed and digital materials provided at Data Fest would be essential for context and history. At The Company's Data Fest, there were more than 20 exhibit booths throughout the meeting space organized in categories: Discovering Data, Using Data, and Protecting Data. At Data Fest, documents were collected by photographing poster boards set up at every booth, table displays, handouts, and computer demonstrations. All poster boards used a template to describe the initiative, including information on the name, purpose, significant activities, efficiencies provided (time, cost, alignment), internal customers, and technology partners. Handouts and displays provided details on engaging with the initiative or accomplishments thus far. Computer demonstrations provided emerging use cases. (We heard at several booths that the demos and handouts had been prepared primarily for the Data Fest and completed just in time for the event.)

Limitations

The project team acknowledges some limitations in the data collection process. First, the project sponsors selected the interview participants, introducing potential selection bias. Second, the project sponsor attended the first few interviews, which may have influenced participants' responses and potentially caused bias, as participants could have held back some of their answers. The project sponsor, however, quickly recognized this issue and decided not to attend the subsequent interviews. Document analysis was added to the data analysis design to provide additional data and balance the insights gathered through the interviews. Additionally, participants self-selected to attend Data Fest, likely indicating a pre-existing positive disposition toward AI and advanced analytics, which may not represent the broader employee sentiment.

The project timeline was another constraint, as it did not allow the extended engagement necessary for a comprehensive understanding of the dynamics and evolving perspectives on AI and predictive analytics within a large global company. The timeline caused a limited number of interview participants, which may also impact the generalizability of findings across the broader employee population of a large company.

Data Analysis

Introduction

This section describes the approach to analyzing the qualitative data obtained from the interviews with leaders and end users at The Company, the observational field notes from Data Fest, and the document analysis collected at Data Fest. The analysis answered the two project questions:

Q1: How is The Company poised to manage change regarding adopting and utilizing advanced analytics?

Q2: In what ways does The Company intentionally use sensemaking to facilitate the adoption of new technology?

Data Preparation and Coding System

The interviews were transcribed through Otter.ai and Fathom. We then transferred the interview transcriptions to MAXQDA, a software program by VERBI Software based in Berlin, Germany, designed for computer-assisted qualitative and mixed methods data, text, and multimedia analysis. This software facilitated the systematic coding of the interview transcripts, data organization, and analysis. (See Appendix C for a description of using artificial intelligence tools in academic research.)

The coding process involved categorizing transcript data into predefined codes aligned with the conceptual framework. For example, we utilized the codes aligned with the ADKAR model for question one regarding change management. "Segment(s)" refers to sentences or phrases we coded with these codes. The codes included:

- Sensemaking
- Negative Narrative

- Positive Narrative
- Change Management: Awareness
- Change Management: Desire
- Change Management: Knowledge
- Change Management: Ability
- Change Management Reinforcement

Data Analysis Approach

We thoroughly examined our data through discourse, thematic, and sentiment analysis. Specifically, discourse analysis was utilized to explore how meaning was constructed through language (Ravitch & Carl, 2019), particularly during observations at the Data Fest. Thematic analysis was applied across all data collection methodologies to identify recurring themes that addressed our project questions (Ravitch & Carl, 2019). Sentiment analysis was used to assess the positivity and negativity of statements, providing some quantitative analysis of feelings toward advanced analytics while understanding the limitation of needing context for the sentiments (Nanli et al., 2012).

Data Organization

Utilizing the QTT (Questions-Themes-Theories) method via MAXQDA, we assigned a "worksheet" to each project question to stay organized throughout our data analysis process. These worksheets held our segments coded from the transcripts from the interviews.

For the document analysis, we scanned and sorted all photographs using a Google Slides template to analyze the documents. Each slide included one to three photographs of a booth display. We coded each slide, noting the internal customers and words aligned with the sub-codes emerging from the interviews under positive and negative narratives, including Excitement, Value, Safety, Mindsets, Trust, and Literacy. We analyzed the frequency of codes and looked at the accessibility of the materials in terms of understandability and relevancy for key users. We also reviewed the transcripts of the keynote conversations at Data Fest, especially the plenary conversation with senior leadership, to understand the key messages The Company wanted all participants to understand.

The following provides an expanded discussion of our qualitative analysis for each question:

Q1: How is The Company poised to manage change regarding adopting and utilizing advanced analytics?

In this part of the analysis, we assessed the readiness of employees to adopt predictive and prescriptive analytics to answer the question of how The Company is positioned to manage change. We utilized the ADKAR change curve as our tool for measuring this. The ADKAR model—awareness, desire, knowledge, ability, and reinforcement—is the theoretical framework for understanding the human elements of change readiness and adoption within this technological transition. We reviewed the change management segments we coded from our data collection, including:

- Change Management - Awareness
- Change Management - Desire
- Change Management - Knowledge
- Change Management - Ability
- Change Management - Reinforcement

The overall distribution of the segments was analyzed to understand their prevalence within the dataset, as shown in Table 3. Note that “segment(s)” refers to sentences or phrases we coded with the above codes: Awareness, Desire, Knowledge, Ability, and Reinforcement.

Table 3

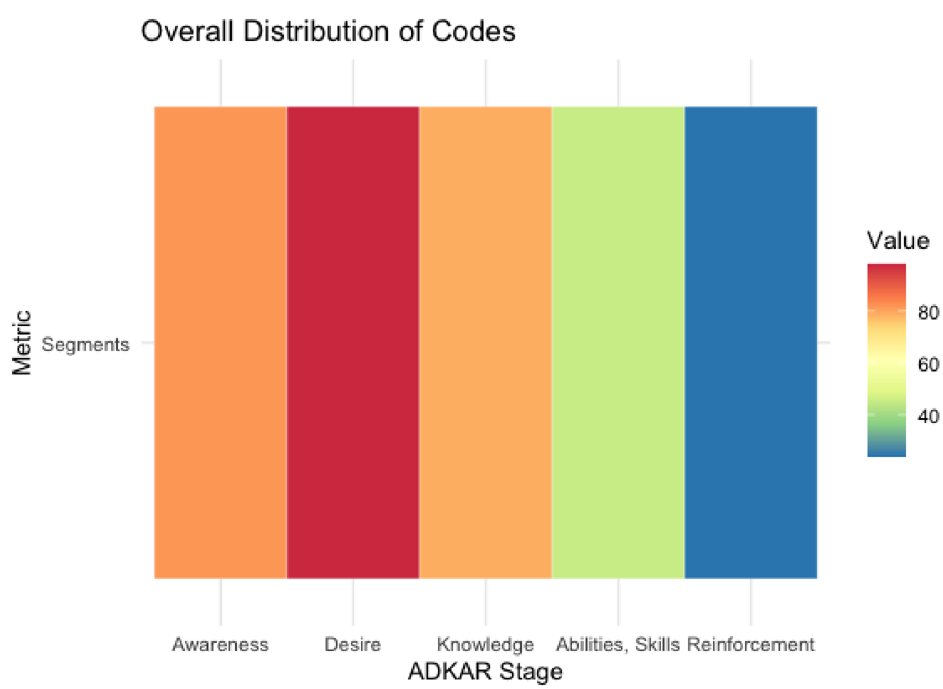
Code Segment Distribution

Code	Segments	Percentage of all codes
Awareness	82	8.7
Desire	98	10.4
Knowledge	79	8.4
Ability	45	4.8
Reinforcement	24	2.5

Analyzing the numbers in the above table, we created a heat map in RStudio to visually represent the distribution of segments across the ADKAR curve within the organization (see Figure 6). Each ADKAR stage is displayed along the horizontal axis, and the colors represent the number of segments from Table 3 associated with each stage. The color legend is included in Figure 6.

Figure 6

Distribution of Codes Heat Map



A key observation from the heatmap is that the desire stage has the highest number of segments, shown in bright red, surpassing the awareness stage, which is different from other enterprise-wide technology transformations. This indicates that employees are excited to embrace this change, but after further analyzing the qualitative segments, we saw they are not necessarily aware of what The Company uses advanced data analytics for and how they can utilize it. As one interviewee pointed out: “So I think it's, the willingness is there, the want is there, how do I get there and what does that mean and how complex is it, is what we are worried about?” (Note: Some quotes are slightly edited for readability.)

We then reviewed the original segments with the same ADKAR codes and chose the most relevant or significant segments that interviewees identified as more important. For example, if an interviewee said that success metrics were a top priority for change adoption, this segment would be coded as a relevant segment under Reinforcement. Another example is an interviewee mentioning the need for basic foundational knowledge, which would be re-coded in the relevant segment category under Knowledge. A total of 274 relevant and significant segments were analyzed from those original codes and categorized according to the ADKAR stages as follows:

- **Awareness:** 58 segments
- **Desire:** 85 segments
- **Knowledge:** 66 segments
- **Ability:** 41 segments
- **Reinforcement:** 24 segments

Continuing our qualitative analysis of the significant segments, we noticed the same observation from above that there is a high concentration of segments from the code Desire. The qualitative analysis of these segments indicates employees' high interest and motivation to embrace advanced analytics. As one interviewee highlighted, “There is a high level of excitement and desire among employees to adopt advanced analytics.” At the leadership panel at Data Fest, one leader stated, “Over lunch, I got the opportunity to listen to our earnings call. And if you have a chance to listen to the earnings call, I counted and lost track [of how much AI was mentioned].” This comment indicated excitement about the opportunity of advanced analytics due to the widespread discussion of generative AI benefits.

The lower number of segments in awareness started to show a somewhat different change curve, where employees are skipping over Awareness for the “what” and “how” but going directly to Desire. One interviewee noted, “There is awareness of the need for change but an understanding of the detailed implementation is lacking.” Another one said, “So, is there excitement in it at the leadership level? 100% there is. Kind of don’t know which pistol to shoot first. Do you shoot? It’s, like, hurry up and shoot. Forget about aiming just shoot. There is a little bit of that.” Another one said, “I think for the most part, folks are more open to it. But again, they don’t really understand it.” This helped us further see a disconnect between the awareness and knowledge stages. Across the comments, we also saw efforts at sensemaking as both leaders and end users try to comprehend the strong desire for something that is not entirely understood as a tool or application.

Further analyzing desire, we were participants and observers at Data Fest, where we observed the excitement of over 900+ employees who had self-registered to attend the event.

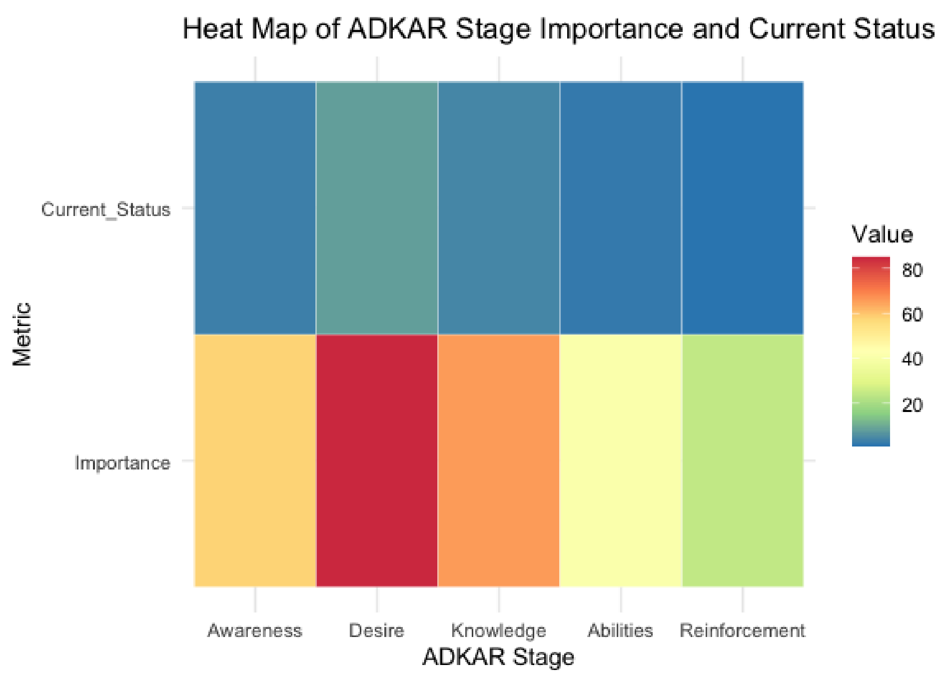
Some notes we wrote down were “crowded,” excited,” “value,” and “lots of energy.” One leader told us at Data Fest, “People are so excited they want to know more.” All three keynotes at the event centered around advanced analytics and generative AI, helping participants make sense of the technology with use cases from other global companies. Although we used “advanced analytics” for prescriptive and predictive analytics in our interviews, “AI” appeared 84 times in 70% of our transcripts.

The desire to adopt advanced analytics is vital; however, foundational knowledge is low, and skills in descriptive analytics are still being developed. In MAXQDA analysis, 70% of the interviews included the words “literacy” and “training,” and 100% included the word “learning,” with more than 100 hits. Interestingly, most of this word frequency came when interviewees talked about descriptive analytics, indicating employees are still working to make sense of their current state. This current state is a notable observation because we were focused on advanced analytics at the beginning of our project and discovered that The Company is still going through a change curve related to descriptive analytics. We were in the early stages of seeing another change curve emerge from our original project plan. This other change curve is descriptive analytics. We will discuss the double change curve in our findings section.

We then created another heatmap in RStudio to visually show where The Company is currently on the ADKAR curve and the importance of each stage for The Company (the future state vision) utilizing the relevant and significant segments in Figure 7. The heatmap uses a color gradient like the one in Figure 6 to indicate the value of each metric, with warmer colors representing higher values and cooler values representing lower values. The importance metric highlights how critical each stage is perceived from the qualitative analysis, while the current status metric indicates the current state of each stage. The heatmap allows us to visualize employees' current state of where they are on the change curve in adopting advanced analytics (the bottom) and the future state vision of what they find most important for their employees to be at (the top). We considered phrases indicating "excitement" or importance to be a positive narrative, appearing more often in the Desire conversations, and comments about concerns or unknowns to be negative narratives, appearing more often in the Awareness discussions.

Figure 7

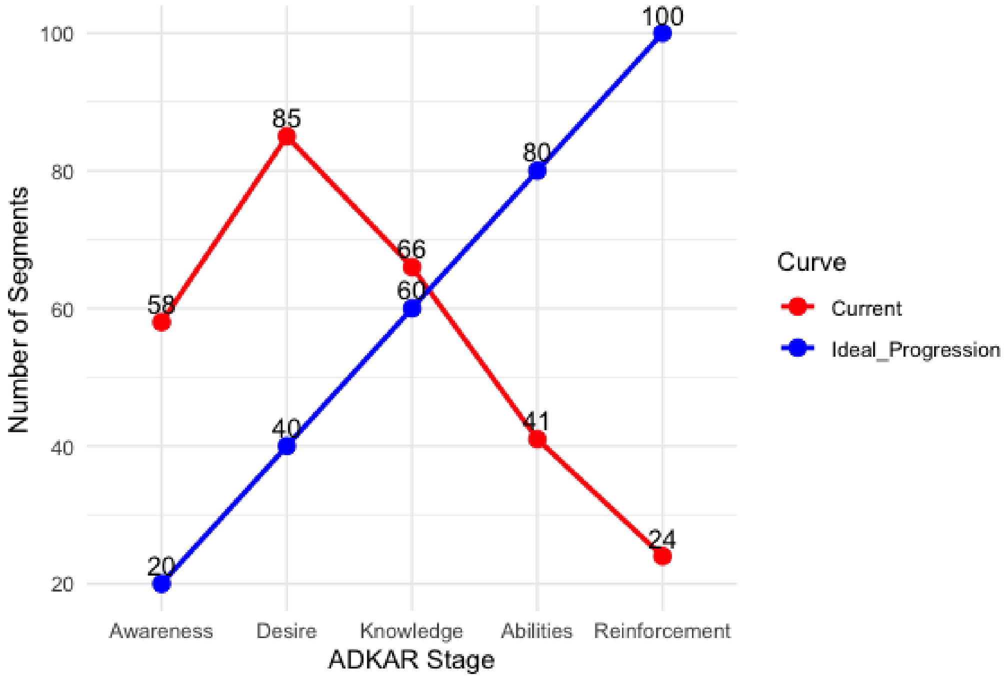
ADKAR Stage Importance and Current Status Heat Map



We then compared The Company's current location in ADKAR to the ideal progression of the ADKAR stages. Figure 8 visually represents the distribution of significant or relevant segments across the ADKAR stages within The Company.

Figure 8

Comparison of Current and Ideal ADKAR Change Curves



The red line indicates the current state, showing how employees progress through awareness, desire, knowledge, ability, and reinforcement. An increase in desire suggests high motivation and interest in adopting advanced analytics. However, awareness is lower, and combined with our qualitative analysis of the segments, we see that employees are unaware of how The Company will proceed with this change. We also see a gap between awareness and knowledge. This gap shows us that employees need that foundational knowledge to progress.

In contrast, the blue line represents the ideal progression, where segments steadily increase from awareness to reinforcement, reflecting a balanced and systematic approach to change management. The Prosci ADKAR Model emphasizes the need for progression: "The goals or outcomes defined by ADKAR are sequential and cumulative. They must be achieved in order" (Prosci Inc., 2016, p. 4). The ideal curve would be that each stage could build upon the previous one, ensuring a comprehensive understanding and reinforcement of new practices for successful change adoption. This analysis highlights the discrepancy between the current state of The Company and the need for targeted interventions to enhance awareness and foundational knowledge to reinforce the change for long-term success. This analysis in MAXQDA and RStudio gave us an understanding of The Company's readiness for adopting advanced analytics by visualizing where they are in the ADKAR Change Curve and then seeing what is needed for the future state.

Lastly, we summarized the qualitative insights utilizing the MAXQDA AI Summary Insights feature from the segments in Table 4.

Table 4

ADKAR Qualitative Insights

ADKAR Stage	**Insights**
Awareness	There is a general awareness of what advanced analytics is globally and why it is essential. However, at The Company, while there is awareness of why the shift toward advanced analytics should happen, there is a lack of detailed understanding of what the shift entails and how to implement it. Employees are exposed to the broader concept from AI's worldwide excitement but not The Company's specifics.
Desire	There is strong excitement and motivation to adopt advanced analytics. Interviewees expressed high excitement and a desire to engage with new technologies. However, the urgency to act on this desire is low to medium, with a need for empowerment, trust, and relevancy.
Knowledge	The overall knowledge level is low. There needs to be a more foundational and basic understanding of data literacy. The Community of Practice is viewed positively. Middle managers need to learn the basics of analytics and leadership skills to guide their teams. There must also be cohesive language between the business and information technology (IT) teams.

Ability	The abilities required for this change are low, and the organization is not ready for training yet. The Company heavily relies on subject matter experts, and there is a recognized gap in the ability to perform advanced analytics without foundational knowledge. An infrastructure must support the upskilling process and a role-based training program.
Reinforcement	Defining use cases and measuring success is not there. There is a focus on the broader impacts of advanced analytics but not the detailed aspects to measure.

Q2: In what ways does The Company intentionally use sensemaking to facilitate the adoption of new technology?

To explore the intentional use of sensemaking, we manually coded all segments focused on storytelling, explanations, or instructions as "General Sensemaking," resulting in 371 segments. We manually coded across the interviews for generally positive and negative narratives to assess the potential use of antenarratives in moving the organization to an unknown future (Poudel, 2019). To augment this effort, we utilized MAXQDA's feature to auto-assign "sentiment"—also called "opinion mining"—based on algorithms that identify words indicating feeling, attitude, or emotional tone.

As the data landscape is quickly emerging, we sought the most up-to-date presentation materials for document analysis to understand the public narrative on data. There is evidence that The Company is employing sensemaking intentionally, notably seen in the public-facing Data Fest, but several interviewees spoke about creating their messages and examples to the best of their abilities without guidance. At Data Fest in the spring of 2024, employees absorbed the carefully curated booths and messaging from the main stage. The Company's investment of time and expenses was evident. The lead organizer explained the event's purpose: "We have to know how to tell a story with data or [we will not get] beyond our competitors." Each booth poster articulated the internal audience for the specific tool or approach, justifying a “What is in it for me?” (WIIFM) strategy. One leader explained the strategy to make subject matter experts explicitly part of the sensemaking strategy:

> *One of the very early things we identified is that you got to get these key voices in here. And then you pull them in, you make them a part of the project...because guess what? It's really hard to complain about change and the new way of working if you were the one who did it.*

Nearly half of the interviewees mentioned the power of story. One said, “We can help tell the story [that] there's real benefit here.” The need to clearly explain the potential of advanced analytics was evident; however, when talking to those who could bridge the main data office with the business units, they seemed to employ sensemaking to the best of their ability without a clear strategy:

> *I found honestly that a lot of the best use cases have come from...shadowing some of the business users and learning where their problems are at where they struggle with it? With things and kind of seeing where are they doing that they have to go back and forth what's going to actually make an impact on what they're doing?*

The examples generated in the field proved invaluable to deepen understanding and engage more users in advanced analytics. A different analyst explained:

> *I would say we have done, like, several broad efforts—not retraining—but reinvigoration sessions where we're meeting with hundreds of users and showing them some of the value that [a specific tool] brings. Now we have business users who can say, ‘Hey, I built this thing. Here's what it does here. [Here’s] how it helps our business.’ We've been doing kind of this road show with different divisions and putting together actual examples.*

For some, this "build it while you are flying" approach was invigorating and a stimulating creative exercise; for others, it was frustrating and challenging.

Thematic Analysis

Across the interviews, we analyzed themes, looking for how interviewees interpreted or made sense of advanced analytics in their context. We read all the coded segments and interpreted them for intent. Then, we tested the strength of those themes with a word count analysis in Table 5. “Value” (67 hits) was the most prevalent theme in sensemaking, followed by “trust” (24 hits). Next, we applied these themes in the document analysis to see if the printed materials at Data Fest reflected the same ideas.

Table 5

Frequently Used Words Related to Sensemaking Overall

	Hits	Related words/meanings
Value	67	Impact Savings Quality
Trust	24	Data quality Job security Change process/unknowns

Value emerged as a critical driver, emphasizing the necessity of sensemaking to advocate for adopting advanced analytics effectively. In many instances, there was a binary choice that the analytics either had value or did not have value. One leader explained, “We get them to see the return on their investment and kind of being able to truly show them the true instrumental value.” Another stressed that their team had “nailed it” in explaining value. However, other leaders did not see a binary; they viewed the discussion on value as surface and depth and cautioned against “hype”:

> *I don't think the challenge is that we have to convince people that this is a good thing. I think the challenge is the other way around, where people can attribute all sorts of value to something that may or may not have any value at all.*

Another leader addressed the tension in building excitement without awareness of what is behind the technology:

> *Because that storytelling, that benefit, that value generation is kind of what would build the hype up, right? But that's something that we always kind of fill out because you know, once you have the insight, somebody really has to do something with it.*

Three interviewees mentioned “value” and “excitement” in close proximity to each other, and two noted concerns about how excitement might mask value that may not be present.

“Value” was applied to multiple levels, from employees to clients. For individuals, it was repeatedly suggested that it would be valuable for individuals to embrace and learn advanced analytics for their job growth and potential in The Company. One leader explained, “I think that [analytics is] really a key space to be like this is something that will help you grow in your career. This is something that will help you do more value-added activity.” For clients, the value was in developing comprehensive solutions and savings. Many interviewees mentioned the “One [Company]” initiative to integrate the multiple business lines at The Company. At Data Fest, the Enterprise Solutions office shared the “One Customer” dashboard, which incorporates master data. The display poster asserted, “Acting as one delivers the best of [The Company] to drive growth.” Another poster declared that the optimization of data would “sav[e] time, miles driven and money!” At the Leader level, they could imagine the potential value of predictive analytics to both the client and the organization:

> *So, there is application throughout commercial finance. I could somehow predict that: hey, based on the customer behavior, they are going to definitely purchase this or not*

purchase this. Either way, having the ability to predict customer behavior would be absolutely awesome and say, hey, are we going to make that sale or not?

For The Company, value translated most often to revenue and cost savings. In the One Customer documents, The Company specifically asked, “Why are we doing this?” and answered that with an enterprise selling solution, which predicted an increase of more than $2.5 billion with the top 35 customers. One end user imagined:

> *I know our current use cases, even though they are very descriptive, we are talking upwards of $5–10 million in dollar savings. So, I can only imagine that, you know, once we move along further, it would, it would be somewhere in and around that, if not more.*

As research shows, trust is essential for data analytics, and narratives are critical to building trust in technology, accuracy, and relevancy of the data, especially in unknown processes (Benbya et al., 2020; Chubb et al., 2022; Davenport, 2018a). Leaders talked about trust as a process and how users needed proof to move forward in their thinking. Referencing the descriptive analytics change curve and the One [Company] initiative, the most recent effort has focused on gathering and cleaning the correct data. “We want to make sure our data is clean even before we talk about analytics,” stressed one leader. With a solid foundation, trust building evolves, especially with generative artificial intelligence. The models will develop as they are used, explained one leader, and it takes time: “Once you have people trust in the data, being able to just ask these one-off questions, then you can start building these models and doing this more predictive stuff...like with technology adoption really that trust and verify aspect to it.” Accuracy is essential in trust building. Errors erode trust. One leader explained, "Well, that's the classic, right? We...send out a report that's got bad master data. It could be, like, a 5% error rate. Well, then it may become 100% unused. So, it doesn't take a lot if people don't have trust in a report, know, it's like they're going to go from using it to not using it entirely." Finally, explaining the relevancy of data is essential. The Company collects data that can overwhelm people. Leaders are considering how to get more specific about which data to analyze for which challenges. Leaders noted, "We build reports that try to solve too many problems” and added, “It's all about specificity and making it as relevant as possible for the audience.” Narratives that suggest trust and relevancy are more likely to help shift mindsets.

Sentiment Analysis: Positive or Negative?

Sentiment analysis examines—often with the help of computer algorithms—opinions, sentiments, emotions, and attitudes expressed in written language, determining the sentiment polarity (positive, negative, or neutral) of words (Nanli et al., 2012), while thematic analysis looks for word count trends and patterns (Ravitch & Carl, 2019). We applied and combined both techniques by 1) manually coding for positive and negative phrases; 2) using algorithm-aided coding on words considered positive, slightly positive, neutral, slightly negative, and negative; and 3) examining themes within all positive segments and themes within all negative segments.

We started with an overall sentiment analysis across the interviews by roles (lead or end-user), as shown in Table 6. We found that leads and end users use more positive words than negative words, and leads are somewhat more positive than end users.

Table 6

Sentiment on Advanced Analytics

	Generally positive narratives	Generally negative narratives
Leads	74	58
End users	52	38
Sentiments from all study participants	126	96

Then we analyzed all segments coded as “positive” and looked for themes (see Table 7) “Positive narrative is important during times of change and growth,” stressed one leader in response to the question, “Are people generally more positive or more negative about adopting advanced analytics?” Those convincing others to try the analytics emphasized that positive narrative development requires a mindset shift that will not happen immediately. Leaders noted that building positive narratives over time and stressing long-term benefits is critical, as generative analytics can have initial pain points. Another strategy is focused on the non-technical journey of analytics adoption and the need to start small. Two interviewees noted that they observed more positive narratives among younger workers in The Company.

Table 7

Frequently Used Words Within Positive and Negative Sentiments

	Hits	Related words/meanings
Positive: Excitement	14	Excite/exciting Anticipation
Negative: Fear	7	Worry Trepidation

“Excitement” was the most common word in segments focused on positive narratives. Fourteen speakers shared their own excitement and that felt by those around them: “And so, I mean, that's where some of the excitement then comes, delivering on some of that art of the possible, like, just helps to build upon that.” They reported, “If you're talking to leaders, from a business function price standpoint, from a technology standpoint...there's ton of excitement. If you're talking to technologists, there's ton of excitement.” Interviewees indicated that the excitement spreads as one division builds an analytics tool and shares its success with other divisions. One end user stressed the need for positive narratives to support outcomes: “The more prepared one is with a positive narrative, the more positive results can be seen in discussions,” she explained.

Negative narratives were codes when the word or tone suggested pessimism, hopelessness, dissatisfaction, or frustration. Negative narratives included words like “resistance” and “reluctance.” Leaders felt pressed to “prove value.” One leader was resigned: “Some people simply do not like change.” Early frustrations were observed when the tools did not deliver as promised. This was attributed to the challenge of generative technology as a chicken and egg situation where users needed “to buy into the tools before they are valuable.” Leaders noted that some narratives were overly hyped and had conflicting messages, making it challenging to build trust. End users expressed concerns about data quality, availability, accuracy, and frustration with the needed time to learn and iterate with the analytic tools.

Fear was the most common word in negative narratives. Leaders noted a “fear of change” and a “fear of the unknown.” One leader explained how data is currently analyzed in Excel spreadsheets and imagined that for those analysts, there might be a fear of their jobs changing or being eliminated: “So, then there's a little bit of fear that okay, so is my job going to be redundant?” Leaders noted a need to acknowledge worry and trepidation directly.

We conducted an additional analysis of the data to understand the overall impressions of the different stages of change management according to the ADKAR framework. For this analysis, we relied on MAXQDA sentiment analysis of all interviews (not limited to the segments we had manually indicated as positive or negative). The heat map analysis in Table 8 indicates that most people, most of the time, were neutral or slightly positive in the interviews and most often in talking about awareness (72 positive/neutral comments) and desire (85 positive/neutral comments), suggesting more engagement at the beginning of the change curve toward advanced analytics.

Table 8

Sentiment Analysis Across Interviews

Sentiment:	*Positive*	*Slightly Positive*	*Neutral*	*Slightly Negative*	*Negative*
Awareness	6	26	40	4	2
Desire	12	41	32	7	1
Knowledge	3	28	30	1	
Ability	1	4	4		
Reinforcement	4	10	6	1	
Sum	26	109	112	13	3

A limitation of the sentiment analysis approach was that sometimes comments had mixed messages, in which the speaker used positive words, but the meaning of the segment expressed skepticism or concern. Another limitation was potential bias in interpreting positivity and negativity. The analysis software MAXQDA offered an AI-generated sentiment analysis, which we ran to test our judgment. According to MAXQDA trainer Alicia Taylor, while computer-generated sentiment analysis can confirm trends and add depth of understanding to manual coding, it has a limitation in understanding context or mixed messages (personal communication, June 9, 2024). We mitigated this concern with a deeper analysis of the interview transcripts. Each researcher coded half of the interviews manually, seeking positive and negative narratives, and then the other researcher reviewed the other's approach and coding, seeking inter-rater reliability.

Findings

Throughout this study, we sought to understand where The Company's readiness for adopting advanced analytics and how sensemaking was intentionally employed to advance employee mindset from reliance on descriptive analytics to embracing predictive and prescriptive analytics. We found that The Company is managing an enormous amount of change simultaneously, and employees are cautiously excited but lack specifics on what they need to do to advance through a change curve. Table 9 shows the significant findings from our data analysis and alignment with the study questions. They provide an understanding of The Company's current state assessment and lay the groundwork for adopting advanced data analytics for a competitive edge.

Table 9

Findings in Relation to the Study Questions

Study Question	**Finding**
Q1: How is The Company poised to manage change regarding adopting and utilizing advanced analytics?	F1: The Company is in the midst of a double change curve. Employees are still learning how descriptive analytics will help their work while being asked to embrace predictive and prescriptive analytics. F2: The Company employees have a high level of desire, but there is more desire than awareness of specifics on advanced analytics, suggesting a new change management methodology.
Q2: In what ways does an intentional focus on sensemaking help The Company speed the adoption of new technology?	F3: The Company lacks a centralized approach to sensemaking with a focus on value and use cases for different divisions.

Finding 1: The Company is in the midst of a double change curve. Employees are still learning how descriptive analytics will help their work while being asked to embrace predictive and prescriptive analytics.

As we analyzed the readiness for change in adopting advanced analytics, another change curve started to come into focus for us. As people discussed the need for “knowledge, skills, and abilities,” the conversations were more often focused on descriptive analytics instead of advanced analytics. The baseline of knowing and using descriptive analytics is still maturing.

The Company's current state reflects a critical point in time characterized by a dual transition in its analytics capabilities. Employees are simultaneously acquiring proficiency in descriptive analytics while being introduced to predictive and prescriptive analytics. The Company is setting up its infrastructure and foundational data while employees are excited and eager about advanced analytics. This simultaneous progression is conceptualized as a double change curve presented below. The visual in Figure 9 represents the overlapping curves of where employees are for descriptive analytics (top) and advanced analytics (bottom).

Figure 9

Overlapping ADKAR Curves Happening in The Company

Currently, The Company is at a stage where employees are developing abilities and skills regarding descriptive analytics, and there is no reinforcement of success metrics in descriptive analytics, which the leaders stated they want to strive for with the organization. One leader stated,

> *And I think one of the biggest things that I think is key in setting this analytic journey is making sure that when we're starting to identify these use cases, we are very, very strict in the sense of defining success, what those measurements are, and how do you know when to pivot into change?*

Foundational knowledge is crucial, as it sets the stage for more advanced analytics. This dual transition between the desire for advanced analytics and still gaining capabilities of descriptive analytics is the in-between time highlighted in Figure 9 above. The in-between time is when the Company experiences unknowns and uncertainties while at the same time, foundational basics are built. From the literature, we learned that the in-between times will be crucial for leaders to manage the change and create a practice of sensemaking (Agrawal et al., 2022).

Despite the desire to adopt advanced analytics, the foundational understanding of descriptive and advanced analytics is still developing while The Company gets the data ready to utilize. One leader emphasized,

> *First and foremost, we have to get that [foundation and basics] solved before we can even talk about analytics. But once we can have a solid foundation, a true master set of data, we can advance when it comes to our customers.*

This lack of readiness for foundational data and the strong desire means that employees are optimistic but lack clarity on the detailed "what" and "how" aspects of the change. A few end users mentioned, "It's too broad," highlighting the need for more specific training on the basics of descriptive analytics before advancing to predictive or prescriptive analytics.

This double change curve for The Company's analytical journey signifies a critical period of transformation, unlike other technology transformations in the workplace. Generative AI and its popularity in personal and professional spaces have employees jumping to the next change curve before progressing through the current one. Employees are progressively learning descriptive analytics, and leadership is creating the data infrastructure at The Company while adapting to the quick-paced and evolving landscape of predictive and prescriptive analytics. One technology leader explained,

> *People are ready for it. Even businesspeople with no firsthand technology experience have heard of ChatGPT, and they are using it in some way. So, I feel that my personal opinion as a technology leader for The Company is that I don't think I've had to convince anybody that using predictive and prescriptive analytics or furthering their business is a good idea. In fact, I'm spending most of my time fighting off people who think that there's some kind of AI magic that can tell them what they need to do.*

Foundational data readiness and foundational learning on the data were the barriers we found hindering The Company from advancing to the next curve. This technology leader continued by saying,

> *And I'm telling them that I don't know if we have the data to give you those answers. That's, that's more me kind of holding people off saying we're not ready and we're still trying to figure some of these things out. As opposed to people saying that I'm not ready to adopt what you're bringing me.*

The dual focus on both descriptive and advanced analytics is essential for fostering a data-driven culture and data-led decision-making the leaders envision.

Finding 2: The Company employees have a high level of desire, but there is more desire than awareness of specifics on advanced analytics, suggesting a new change management methodology.

Finding two suggests a revised approach to a change management methodology, differing from traditionally going through the ADKAR steps in sequential order, but rather capitalizing on the desire The Company has already developed to build awareness and knowledge. Employees of The Company showed a high level of desire to engage in advanced analytics, yet this desire exceeds the level of awareness regarding the specific use cases of The Company's AI-powered tools for advanced analytics. Since our analysis utilized the ADKAR model as a foundational tool to evaluate the readiness for change, we will share our findings on where The Company is at for each stage before we discuss the new methodology.

Awareness: The Company lacks awareness regarding specific use cases of advanced analytics but is generally aware of generative AI. The awareness of The Company's specific use cases varies significantly across different levels and departments. Leadership demonstrates a high level of awareness and actively pushes for adopting advanced analytics. However, the broader team of end users exhibits varied levels of specific awareness, with some employees familiar with tools, reports, or projects while others are not. The employees at The Company understand the need to shift toward advanced analytics, which is the desire stage, but lack the detailed knowledge and awareness of the specific "what" and "how" of these tools.

Desire: Employees' desire and excitement to adopt advanced analytics is high. The concept of WIIFM is crucial for sustaining this desire (Jöhnk et al., 2021) as The Company moves forward with putting use cases in place. For example, one interviewee stated, "There is a high level of excitement and desire among employees to adopt advanced analytics. However, [they] also need the importance of relevancy and trust to sustain this."

Knowledge: Knowledge of advanced analytics among employees is generally low, with a significant need for foundational learning. Foundational knowledge is essential for effectively managing change (Cummings et al., 2016). The analysis showed a connection between awareness (for the specific use cases) and knowledge (basic education) in The Company's placement on the change curve. One interviewee stated, "Employees need to understand the problems that advanced analytics will solve and have access to a library of use cases and an FAQ System." This statement emphasizes the need for practical knowledge and a basic level of awareness to gain knowledge of advanced analytics.

Ability: The ability to apply advanced analytics is low across the organization. Employees rely heavily on subject matter experts (SMEs) for current descriptive analytics reporting and lack the skills to utilize these tools effectively. We also found that middle managers must be upskilled to lead changes efficiently, including learning empowerment and not "just doing what is told of them,” one leader pointed out. The "ability" phase is crucial because it involves developing the new skills and behaviors necessary to implement the change daily, often requiring ongoing coaching and support (Hiatt, 2006). We did find that role-based training will be the preferred training methodology; however, The Company is not ready for official role-based training, as expressed by the community of practice leader and project sponsors. Speaking to leaders, we found that adequate infrastructure and foundational knowledge will be needed before implementing an official training pathway.

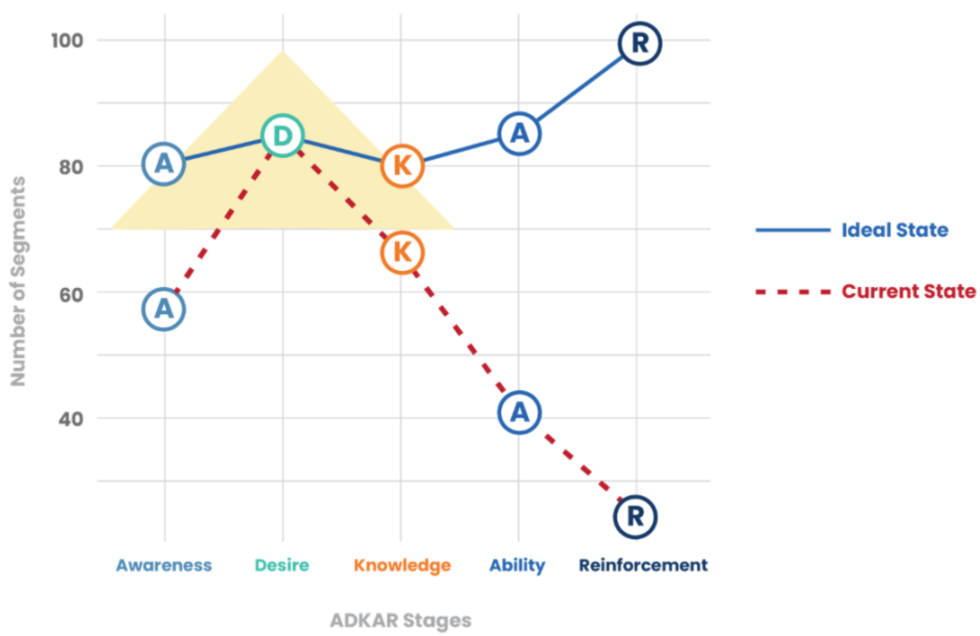
Reinforcement: While we found leadership to be aligned and supportive, a part of the reinforcement stage, reinforcement regarding metrics, was low. We found that continuous advocacy and a top-down approach with leadership alignment are currently present, but to maintain momentum and capture the impact, there needs to be a robust evaluation system with metrics (Kanitz et al., 2023). Defining success metrics and regularly reviewing and adjusting strategies based on these metrics can reinforce positive behaviors (Appelbaum et al., 2012). One leader stated, “Defining success metrics and strict measurement criteria are crucial for tracking progress and making necessary adjustments.”

Reviewing the placement of the employees on the ADKAR change curve emphasizes the need to redefine the change management methodology for The Company, focusing on enhancing awareness of use cases and increasing foundational knowledge simultaneously to support the employees’ strong desire for change. In a traditional change management strategy, the focus is on helping people adopt the technology, and the leaders are utilizing techniques to prepare employees for adoption. However, with this change curve, people already have the excitement and readiness for the change but lack awareness, data readiness, and basic knowledge. Capitalizing on the desire while focusing on the connection of awareness and knowledge will help The Company progress to its ideal future state.

The graphic in Figure 10 was created from the Figure 7 heat map in the analysis displaying The Company's current state on the ADKAR Curve and the important segments creating their ideal state. The triangle around awareness shows the connections between awareness, desire, and knowledge. This triangle suggests that The Company needs to capitalize on desire and focus on boosting awareness and knowledge. This helps us understand where The Company should place its time and energy and how we can infuse sensemaking to advance them through the curve. We will discuss this more in recommendations.

Figure 10

The Company's Current State and Ideal State



Finding 3: The Company would benefit from a centralized, collective approach to sensemaking with a focus on value and use cases for different divisions.

A great deal of sensemaking is happening, generating excitement, but from our observations and conversations, there does not appear to be a centralized, strategic, intentional focus on sensemaking. With significant excitement but less awareness of the practicalities of advanced analytics, employees lacked standardized messaging and expressed a need for a standardized approach to developing use cases. It appeared that members of the Global BI team are constantly translating between the Enterprise Data Team and the business units. Analysts employed different strategies to explain advanced analytics and develop examples. One notable strategy was an employee using an adapted "Gemba walk," a tactic developed by Taiichi Ohno, a Japanese industrial engineer in the Toyota Production Process (Gesinger, 2016), to observe, recognize, and communicate how the office was using advanced analytics. No one mentioned a central messaging source or support for sensemaking.

Leadership shared their concerns that much of the current understanding of analytics is relatively shallow and potentially hyped. One senior leader noted, “This is at the height of the hype cycle, right? So yeah, there is way more value attributed to it than reality.” However, there appear to be small steps to deeper understanding. One participant in Data Fest exclaimed, “I thought Data Fest would be a contradiction in terms, but it turned out great.” The good feelings generated by the potential for the new technology allowing advanced analytics will help the sensemaking spark throughout The Company. While it is just beginning, as one leader noted, we need to “evolve and adapt” as our understanding of the potential grows.

At Data Fest, we heard that people create narratives to the best of their ability based on their experience and expertise. There was an interesting contrast between those who had been at The Company for many years and those under two years of tenure. Newer employees were able to provide more context for the shift to advanced analytics, while more tenured employees were quicker to talk about use cases and building examples. With more experience, analysts could provide examples from other offices: “I think it's seeing actual things their peers have created. When we say, ‘[analytics] can do this,’ it does not resonate.” Both newer and more tenured employees agreed that “people want something tangible that they know is going to drive value”; they were looking for concrete examples and impact statements.

Our findings indicate that employees wanted time and resources to help develop narratives centered around value themes supported by illustrative use cases. Employees described wanting narratives that are practical, relevant, specific, realistic, simple (jargon-free), and repetitive. One leader said the current messaging is “positive but fluffy” and asked for substantive messages and examples. Some employees cautioned that fully standardized use cases would be unhelpful as narrative variations are essential to enhance sensemaking across different audiences and business units. One employee described needing a repository: “I say we should have a library of historical and analytics because that would help to get to that predictive a little bit quicker.” Another leader said a library is jammed with content, but “there has to be an interaction piece to it.” When assessing something missing, the size of the interview pool was a limitation. Further research and a communications audit would provide more evidence of the availability and depth of messaging available.

Recommendations

As The Company starts integrating advanced analytics into its operating model, providing actionable recommendations to facilitate transformation moving forward is essential. The following recommendations in Table 10 address the findings connected to both project questions. The recommendations in the third column align with the findings and support The Company through the transition from descriptive to advanced analytics.

Table 10

Relation of Study Question to Finding to Recommendations

<table>
<tr><th>Study Question</th><th>Findings</th><th>Recommendations</th></tr>
<tr><td>Q1: How is The Company poised to manage change regarding adopting and utilizing advanced analytics?</td><td>F1: The Company is in the midst of a double change curve. Employees are still learning how descriptive analytics will help their work while being asked to embrace predictive and prescriptive analytics.

F2: The Company employees have a high level of desire, but there is more desire than awareness of specifics on advanced analytics, suggesting a new change management methodology.</td><td rowspan="2">Adopt an AI-specific change management approach infused with sensemaking.

R1: Navigate the in-between times between descriptive and prescriptive analytics, building foundational knowledge to support the move toward advanced analytics.

R2: Create an internal communication strategy with a sensemaking toolkit emphasizing value and trust, including dynamic use cases.

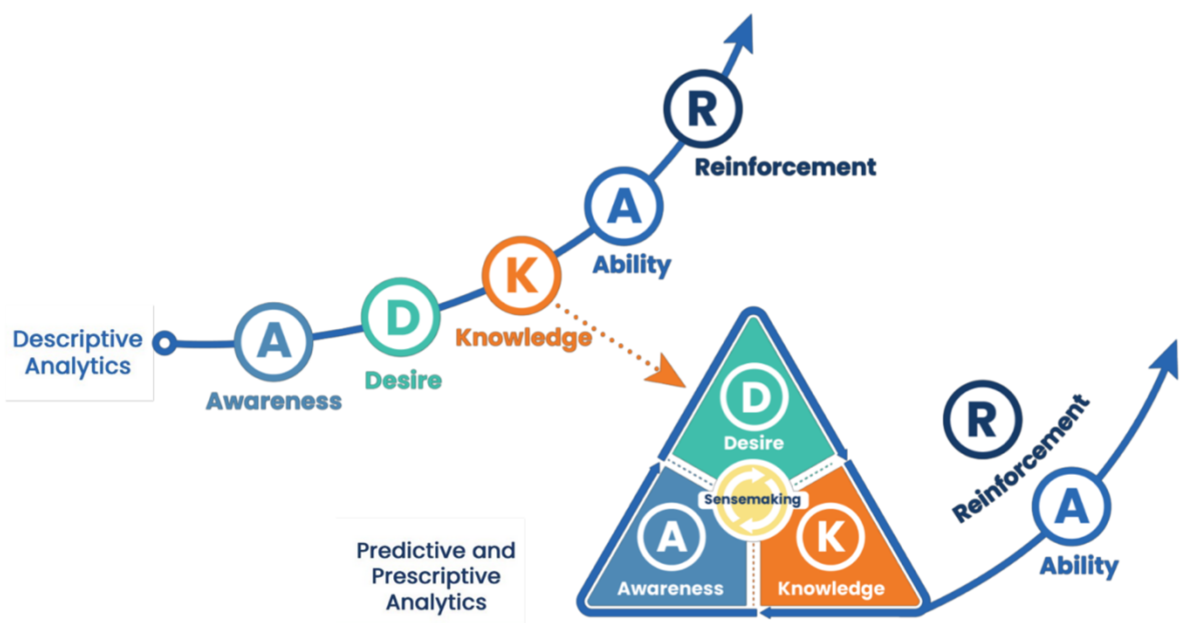
R3: Integrate training with success metrics.</td></tr>
<tr><td>Q2: In what ways does an intentional focus on sensemaking help The Company speed the adoption of new technology?</td><td>F3: The Company lacks a centralized approach to sensemaking with a focus on value and use cases for different divisions.</td></tr>
</table>

Recommendation: Adopt an AI-specific change management approach infused with sensemaking

Considering our findings on the dual change curves and the readiness of The Company employees to adopt advanced analytics, we recommend an AI-specific change management methodology and strategy. The methodology is the framework in Figure 11, and the strategy is the roadmap in Figure 12. Both combined are the change management approach. This approach will leverage the existing excitement for generative AI while building foundational knowledge in descriptive analytics and awareness of the use cases. The proposed change management methodology and strategy will encompass tangible action items to foster a data-driven decision-making culture.

Figure 11 illustrates the change management methodology, which combines the findings of the dual change curves with a new approach to fostering AI and advanced analytics adoption.

Figure 11
Adapted Change Management Methodology



This image combines two change curves of the continued development of descriptive analytics adoption (top line) and the progression toward advanced analytics (triangle and lower line). The “AI Change Catalyst Loop” triangle in the center signifies the intersection where employees’ desire for advanced analytics must be capitalized on to build on awareness and knowledge. This triangle is infused with sensemaking to enhance the progression toward adoption faster and more efficiently. There is a connection between learning descriptive analytics (knowledge) and the desire for advanced analytics and, eventually, gaining knowledge for advanced analytics. This connection helps The Company define success metrics in the abilities and reinforcement stage. The new methodology emphasizes combining reinforcement with ability, suggesting that The Company should start integrating success metrics with training. This dual approach with reinforcement and ability stages aims to create a continuous feedback loop of learning and application.

We recommend a three-phase change management strategy to navigate this new approach. This strategy is designed to leverage the excitement for generative AI while building a foundation in data analytics. The phases include addressing the gap during the in-between times, enhancing internal communication through sensemaking, and integrating training with business and success metrics. The three phases are shown below in Figure 12.

Figure 12

Proposed Change Management Strategy for The Company

R1: Phase 1 - Bridge the Gap: Foundations for an Analytics Journey

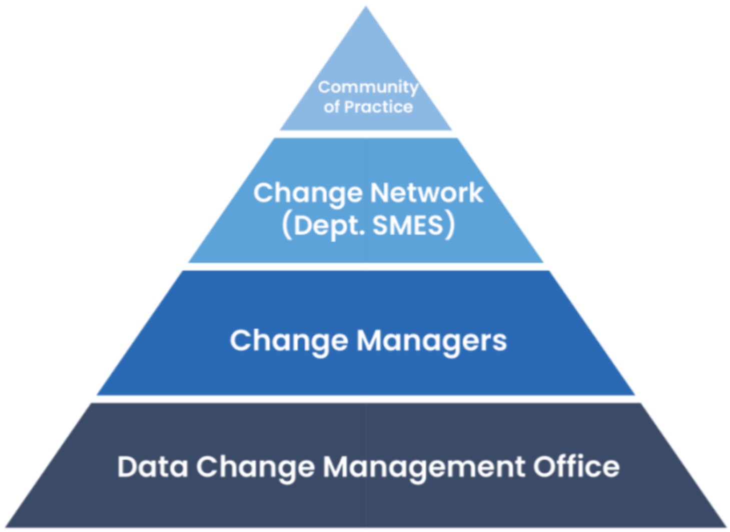
This phase addresses the transitional period when employees simultaneously build foundational knowledge in descriptive analytics while being introduced to predictive and prescriptive analytics. Davenport (2018a) pointed out this leading tail as a company moves from Analytics 3.0 to 4.0 (see Figure 2). Employees noted their current focus on building trust in descriptive analytics first, even though they are excited about what is next. The goal in this phase is to harness the desire and enthusiasm for advanced analytics within the critical intersection identified in the triangle of the new approach, ensuring that employees clearly understand the knowledge and skills required for this transition.

Develop a Data Analytics Change Management Office

We recommend that The Company establish a dedicated office within EDO responsible for the ever-changing landscape of data analytics and the transition from descriptive to predictive and prescriptive analytics. Davenport (2018a) calls these a "center of excellence" established to create consistent enterprise guidelines and standards for IP ownership, tools, languages, data formats, documentation, and regulatory issues while acting as internal partners to development and analytics teams and maintaining communication with key stakeholders. As part of this data change management office (see Figure 13), The Company would train department managers as change leaders guiding employees from existing analytics to advanced analytics skills. This structure would equip managers with the skills and knowledge to act as change leaders within their departments and would include training in change management, empowerment, leadership, and effective communication. The next part of this office would be developing a change network program of departmental SMEs who will champion the change efforts of business processes within their respective teams. The Company already has a culture of SMEs, so this would create a more formalized and efficient process.

Figure 13

Recommended Data Change Management Office Structure



Strengthen the Community of Practice

At the top of the change management office infrastructure is the community of practice already established at The Company. We know sensemaking is inherently collective (Ancona, 2012), highly interactive, and collaborative (Lüscher et al., 2006). We recommend providing additional resources to the team running the community of practice since this will be essential in progressing through the awareness, desire, and knowledge triangle of the change curve. Within the community of practice, we recommend strengthening data proficiency through learning pathways. Designing structured learning pathways will guide employees from foundational data skills to advanced analytics.

Invest in Learning Pathways

At the request of the project sponsor, we asked how much time and money leaders would invest in training. We found that employees would learn best through practical workshops, nano YouTube-like videos, and interactive hands-on learning. Researchers like Kanitz et al. (2023) recommend various training and development opportunities, including online courses, workshops, and coaching sessions. These strategies could help reinforce the concepts and ensure employees feel confident using them in their daily tasks while progressing through the analytical journey. The interviewees responded that they would be willing to dedicate 10%-20% of their time to continuous learning. We recommend communicating the importance of continuous learning by allocating 10% of employees' time to this learning pathway. As part of the community of practice, The Company should continue to develop an online platform that serves as a central hub for all materials, process maps, FAQs, keywords, and learnings. The change management office housing the community of practice will need someone dedicated to this website for regular updates.

Facilitate Leadership Alignment and Top-Down Infrastructure

Effective change management requires strong leadership alignment (Wijayati et al., 2022) and cohesive infrastructure to drive and sustain the transition toward advanced analytics. The Company showed high leadership support, shared excitement, and a supportive environment from the leaders to encourage the utilization of advanced analytics. We recommend that The Company implement a structured leadership engagement roadmap with integrated feedback loops to strengthen the leadership alignment further and create a top-down infrastructure. This roadmap would outline clear milestones and checkpoints for leaders to ensure that progress is continuously monitored and aligned with the strategic objectives.

Communicating who the leaders are to end-users will be necessary so that end-users can engage in feedback loops and leaders can adapt and refine strategies based on real-time input from stakeholders.

Developing a shared vision that leadership can clearly articulate and sensemake to their employees is crucial for building trust and relevancy among employees. Leadership should consistently reinforce this vision through various channels, including town hall meetings, internal newsletters, and public events like Data Fest. Maintaining momentum through these events should be leader-led to inspire and engage employees. This leader-led approach will help sustain excitement and reinforce the collective effort toward achieving the shared vision.

Building trust and relevancy requires consistent and transparent communication from leadership, a form of sensemaking. In his research, Kotter (1996) stressed that successful transformation efforts involve using all existing communication channels to broadcast the vision. Executives who communicate well incorporate messages into their hour-by-hour activities, which helps build trust and relevancy. Regular updates and clear communication on use cases will help employees understand the WIIFM, a common buy-in tactic, and trust in the process. The key to sensemaking is storytelling, which helps create a compelling account of the need for change and builds support for the shifts (Appelbaum et al., 2012). Employees in the interviews stated they liked it when their leaders asked them questions, as it made them think more about the process and feel like they were part of its creation.

R2: Phase 2: Cultivate Communication: Narratives to Embrace Change

Effective communication is essential for embedding the change deeply within the organization (Appelbaum et al., 2012; Galli, 2018; Phillips & Klein, 2023). This phase enhances communication through sensemaking and promotes clear, relevant, and impactful messaging. By utilizing narratives, stories, and clear messaging, employees can make sense of the data analytics journey, understand its importance, and see their role within the broader context of the organization's goals. We recommend an internal communications initiative on advanced analytics adoption, including dynamic messaging for key audiences, a sensemaking toolkit for managers to be AI change leaders and a versatile use case library.

In the AI landscape where information is incomplete (Poudel, 2019), The Company needs a commitment to prospective sensemaking in a centralized way, helping leaders and end users examine the probable impact of actions and nonactions (Gioia et al., 1994) using advanced analytics. This type of sensemaking cannot be simply top-down; a collective approach will allow for blending, negotiating, and integrating different perspectives (Dell'Acqua et al., 2023) to achieve a shared aspiration of what is possible and necessary for corporate advantage.

The Company might embrace antenarratives as a key strategic communications tool. Antenarratives are not just pre-narratives; they are active sensemaking tools that help organizations navigate complex changes by integrating prospective (forward-looking) and now-spective (present-focused) insights with retrospective understanding (Boje, 2001, 2011; Poudel, 2019). Antenarratives are the raw, unstructured insights that emerge amid change. They are the "bets on the future" (Boje, 2001, p.1), offering a glimpse into the ongoing, dynamic processes that shape organizational reality. See Table 11 on applying antenarratives in The Company to support change management.

Table 11

Identifying and Applying Antenarratives for Change Management

	Identifying Antenarratives	**Applying Antenarratives**
Awareness	Open communication channels: Set up platforms for sharing experiences.	Detect trends early: Identify emerging trends and issues early.
Desire	Encourage storytelling and use case development: Promote a culture of sharing stories and examples	Capture diverse views: Get multiple perspectives for richer insights.
Knowledge	Conduct narrative interviews and focus groups: Interview employees to gather insights and use thematic analysis Use technology and analytics in communications: Leverage tools to analyze communication data.	Stay agile: Remain flexible and responsive to changes.
Ability	Monitor informal networks: Pay attention to informal communications.	Foster innovation: Encourage new ideas and creative solutions.
Reinforcement	Use sensemaking sessions: Organize workshops to interpret events. Establish feedback loops: Regularly gather and act on feedback.	Improve engagement: Enhance communication and morale.

Note. Information drawn from Boje (2001, 2011), Hiatt (2006), and Poudel (2019).

In essence, antenarratives offer a strategic tool for navigating the complexities of organizational change, providing early insights, and fostering a culture of continuous adaptation and innovation.

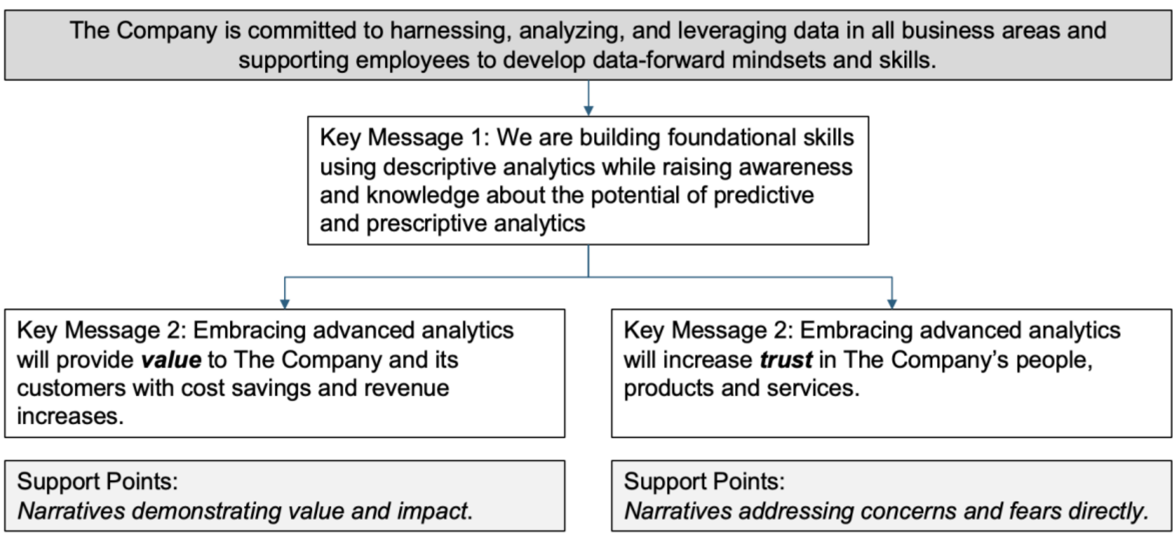
Leveraging Data Fest as a collective sensemaking event demonstrates the organizational commitment to guiding employees through the data analytics change curve. Based on our observations and document analysis, strategies to create Data Fest 2.0 in 2025 might include developing a “road map” for participants to place themselves on the data analytics journey. This roadmap could be gamified by asking participants about their awareness and knowledge of data analytics specifics and then helping participants know which booths to attend. The Data Fest display booths were well-structured and provided valuable information for awareness; to deepen knowledge, Data Fest might include workshops or “use case exploration” where small groups dive deep into scenarios. All materials and presentations should be carefully considered, with messages emphasizing value and trust.

Developing a shared language between the business and IT of the organization is also critical. This shared language involves creating common terminology and understanding to facilitate better communication and collaboration. Workshops and joint training sessions can help establish a shared language. The plan will also include a sensemaking toolkit for managers to help them act as AI change leaders. This toolkit should include resources for facilitating discussions, answering common questions, and creating meaning for employees. The messaging must be “sticky” and effective with sensemaking strategies. A department engagement plan should also be developed to address employees' questions regarding how this change can benefit them, thereby building trust and relevancy. A dedicated internal communications strategist will help leaders shape decks and presentations for end users and share sticky and effective messages across The Company.

Specifically, we recommend a clear message map with dynamic messages that are widely available and transparent throughout The Company. The map should have positive narratives that are practical, relevant, specific, realistic, simple, and jargon-free. Leaders can convey core messages on value and clearly describe its impact. They can also directly address any negative narratives around fear and apprehension. The most critical part of internal communications will be a use case library. Analysts should gather existing cases, assess them for clarity and relevance, and share them broadly with employees. Data managers can then adapt for specific purposes. Figure 14 suggests the beginning of a message map for internal use.

Figure 14

Initial Message Map Approach



Creating a comprehensive library of use cases that illustrate successful applications of advanced analytics within the organization will also be beneficial. This library will be a valuable resource for employees regarding use cases and business processes. Embedding prospective sensemaking throughout the change management process promises to speed understanding, acceptance of unknowns, and, ultimately, adoption of AI-related initiatives (Poudel, 2019).

R3: Phase 3: Integrate Insights: Connecting Learning with Outcomes

Phase 3 of the change management strategy focuses on integrating a training program with business metrics and success indicators established by leaders in the above phases. This phase aims to link employees' training and the outcomes the organization seeks to achieve to be an advanced data-centric organization. This phase is the abilities and reinforcement stage of the curve. By setting clear performance indicators, employees can understand how their efforts contribute to broader organizational goals, fostering a sense of purpose and continuous motivation for sustainment.

Role-based training is essential to maintain relevancy and the WIIFM for individual employees. One interviewee stated,

> *Training is needed on specific things that people do in specific roles. And I think that's where you're really going to get people to adopt the things they're learning is if you're saying, Hey, I know in your role, you have these problems that come up, this is a problem, or this is how you could build it. And so, it's really for me, it's all about specificity, and making it as relevant as possible for the audience.*

Each training module should be tailored to the end users' specific use cases and business processes, and employees should be trained in what is directly applicable to their daily tasks. Role-based training addresses the WIIFM sentiment, builds trust and engagement, and creates faster adoption.

Finally, alignment of individual performance with company culture supports change sustainability and integration (Phillips & Klein, 2022). Training tied to culture and company metrics should address employee behaviors, attitudes, capabilities, and commitment to change (Beer & Nohria, 2000). Notably, the research also indicates a need to monitor individual and team buy-in and performance as a reinforcement strategy (Galli, 2018). With strong leadership alignment, a commitment to training, and an emphasis on culture, The Company is well-positioned to focus on sustainment in the data analytics journey.

Conclusion

At the time of this submission in July 2024, the adoption of generative AI is exploding. AI integration is changing how people work across functions across industries, notably in marketing, sales, and product development (McKinsey & Company, 2024). In a 2024 global survey, McKinsey & Company reported that 65% of respondents said their organizations regularly use AI, and there are clear material benefits in increased revenue and decreased costs. The moment is to pay attention to integrating this technology across The Company.

However, it pays to have patience with people in moments of urgency. Change expert Kotter (1996) stressed that rushing through the initial phases of change and pushing people out of their comfort zones too quickly will lead to failure. People are critical, especially with generative AI, as AI generates better outcomes if people are thoughtful about training and shaping it. For The Company, we hope they will harness the apparent excitement and energy to build skills for AI-driven transformation quickly.

We can draw from the past to understand our current precipice and how adoption might happen (Weick, 1995). For example, from Volta's invention of the electric battery (1800) to the opening of the first electric factory (1881), there was no obvious roadmap for 80 years, but excitement slowly built as the use of light bulbs spread (Agrawal et al., 2022). Today's transformation with artificial intelligence can feel overwhelming and scary to employees, so it is even more critical for leaders to engage in intentional sensemaking. Bricolage—an approach to manage unexpected situations by combining existing elements in novel ways—offers a frame for The Company's leaders to be creative in this time of unknowns, encouraging them to depend on their leadership skills and organizational culture to create the emerging map for moving forward (Weick, 1993).

The project offers insights into how a linear approach to change management is likely insufficient in this period of transformational technology adoption. A new AI Change Catalyst Loop combines and layers ADKAR's familiar phases of awareness, desire, and knowledge in creative and resourceful ways to build momentum for adoption, a form of bricolage. With a new change management approach developed based on employee insights, The Company has an opportunity to propel the adoption of advanced analytics and other AI tools. In a time characterized by urgency, The Company will thrive with constant attention to this change-based momentum, and its presence or absence will determine the ultimate success of AI-driven transformation (Appelbaum et al., 2012).

AI is transforming human society in fundamental and profound ways (Agrawal et al., 2022; Chubb, et al., 2022; Kissinger, et al., 2021; McKinsey & Company, 2023). In this case study of one company, we were able to glimpse the coming changes and consider the human need to embrace and adopt AI as a tool and partner in ongoing work. Only by respecting the human emotions of excitement and fear of this new technology will we be able to build and explain our map moving forward. We are eager to help shape this new future.

References

Agrawal, A., Gans, J., & Goldfarb, A. (2022). *Power and prediction: The disruptive economics of artificial intelligence*. Harvard Business Review Press.

Ancona, D. (2012). Sensemaking: Framing and acting in the unknown sensemaking. In S. A. Snook, N. Nohria, & R. Khurana (Eds.), *The handbook for teaching leadership: Knowing, doing, and being* (pp. 3–19). SAGE Publications.

Appelbaum, S. H., Habashy, S., Malo, J.-L., & Shafiq, H. (2012). Back to the future: Revisiting Kotter's 1996 change model. *The Journal of Management Development, 31*(8), 764–782. https://doi.org/10.1108/02621711211253231

Bargar, R. R., & Duncan, J. K. (1982). Cultivating creative endeavor in doctoral research. *The Journal of Higher Education, 53*(1), 1–31. https://doi.org/10.1080/00221546.1982.11780422

Bedué, P., & Fritzsche, A. (2022). Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption. *Journal of Enterprise Information Management, 35*(2), 530–549. https://doi.org/10.1108/JEIM-06-2020-0233

Beer, M., & Nohria, N. (2000). Cracking the code of change. *Harvard Business Review, 78*(3), 133–141.

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *MIS Quarterly Executive, 19*(4).

Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science, 66*(3), 1025–1044. https://doi.org/10.1287/mnsc.2018.3253

Boje, D. M. (2001). *Narrative methods for organizational and communication research*. SAGE.

Boje, D. M. (2011). Introduction to agential antenarratives that shape the future of organizations. In *Storytelling and the future of organizations* (Vol. 11, pp. 19–38). Routledge. https://doi.org/10.4324/9780203830642-7

Bolman, L. G., & Deal, T. E. (2010). *Reframing organizations: Artistry, choice and leadership*. John Wiley & Sons, Incorporated.

Bridges, W. (1986). Managing organizational transitions. *Organizational Dynamics, 15*(1), 24–33. https://doi.org/10.1016/0090-2616(86)90023-9

Christou, P. A. (2023). How to use artificial intelligence (AI) as a resource, methodological and analysis tool in qualitative research? *Qualitative Report, 28*(7), 1968–1980. https://doi.org/10.46743/2160-3715/2023.6406

Chubb, J., Cowling, P., & Reed, D. (2022). Speeding up to keep up: Exploring the use of AI in the research process. *AI & Society, 37*(4), 1439–1457. https://doi.org/10.1007/s00146-021-01259-0

Cummings, S., Bridgman, T., & Brown, K. G. (2016). Unfreezing change as three steps: Rethinking Kurt Lewin's legacy for change management. *Human Relations, 69*(1), 33–60. https://doi.org/10.1177/0018726715577707

Davenport, T. H. (2013). *Analytics 3.0*. Harvard Business Review. https://hbr.org/2013/12/analytics-30

Davenport, T. H. (2018a). From analytics to artificial intelligence. *Journal of Business Analytics, 1*(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

Davenport, T. H. (2018b). *The AI advantage: How to put the artificial intelligence revolution to work* (1st ed). MIT Press.

Davenport, T. H., & Mittal, N. (2023). *All-in on AI: How smart companies win big with artificial intelligence.* Harvard Business Review Press.

Dell'Acqua, F., McFowland III, E., Mollick, E., Lifshitz-Assaf, H., Kellogg, K. C., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality (Working Paper). Digital Data Design Institute, Harvard Business School.

Dwivedi, Y., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., . . . Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Galli, J. B. (2018). Change management models: A comparative analysis and concerns. *IEEE Engineering Management Review, 46*(3), 124–132. https://doi.org/10.1109/EMR.2018.2866860

Gates, B. (2023, March 21). *The age of AI has begun*. The Gates Notes. https://www.gatesnotes.com/The-Age-of-AI-Has-Begun

Gesinger, S. (2016). Experiential learning: Using Gemba walks to connect with employees. *Professional Safety, 61*(2), 33–36. https://www.proquest.com/docview/1765137209

Gilbert, D. T., & Wilson, T. D. (2009). Why the brain talks to itself: Sources of error in emotional prediction. *Philosophical Transactions of the Royal Society of London: B. Biological Sciences, 364*(1521), 1335–1341. https://doi.org/10.1098/rstb.2008.0305

Gioia, D. A., Thomas, J. B., Clark, S. M., & Chittipeddi, K. (1994). Symbolism and strategic change in academia: The dynamics of sensemaking and influence. *Organization Science, 5*(3), 363–383. https://doi.org/10.1287/orsc.5.3.363

Harmat, V. (2023). The application of the sensemaking perspective for the examination of employees' behavioural responses to the HR chatbot. *Organizacija, 56*(3), 233–246. https://doi.org/10.2478/orga-2023-0016

Harry, M. J., & Schroeder, R. (2000). *Six Sigma: The breakthrough management strategy revolutionizing the world's top corporations*. (1st ed.). Currency.

Hastuti, R., & Syafruddin. (2023). *Ethical considerations in the age of artificial intelligence: Balancing innovation and social values*. West Science Social and Humanities Studies.

Heath, D., & Heath, C. (2010). *Switch: How to change things when change is hard*. Crown Business.

Hiatt, J. M. (2006) *ADKAR: A model for change in business, government and our community*. Prosci Learning Center Publications.

Holt, D. T., Armenakis, A. A., Harris, S. G., & Feild, H. S. (2007). Toward a comprehensive definition of readiness for change: A review of research and instrumentation. W. A. Pasmore & R. W. Woodman (Eds.), *Research in organizational change and development*

(Vol. 16, pp. 289–336). Emerald Group Publishing Limited. https://doi.org/10.1016/S0897-3016(06)16009-7

Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering, 63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

Jones-Schenk, J. (2019). 70% failure rate: An imperative for better change management. *The Journal of Continuing Education in Nursing, 50*(4), 148–149. https://doi.org/10.3928/00220124-20190319-03

Kamila, M. K., & Jasrotia, S. S. (2023). Ethical issues in the development of artificial intelligence: Recognizing the risks. *International Journal of Ethics and Systems*. Advance online publication. https://doi.org/10.1108/IJOES-05-2023-0107

Kanitz, R., Gonzalez, K., Briker, R., & Straatmann, T. (2023). Augmenting organizational change and strategy activities: Leveraging generative artificial intelligence. *The Journal of Applied Behavioral Science, 59*(3), 345–363. https://doi.org/10.1177/00218863231168974

Kissinger, H., Schmidt, E., Huttenlocher, D. P., & Schouten, S. (2021). *The age of AI: And our human future* (1st ed.). Little, Brown and Company.

Kotter, J. P. (1996). *Leading change*. Harvard Business School Press.

Lewin, K. (1951). *Field theory of social science: Selected theoretical papers.* Harper & Brothers.

Lüscher, L. S., Lewis, M., & Ingram, A. (2006). The social construction of organizational change paradoxes. *Journal of Organizational Change Management, 19*(4), 491–502. https://doi.org/10.1108/09534810610676680

Maitlis, S., & Sonenshein, S. (2010). Sensemaking in crisis and change: Inspiration and insights from Weick (1988). *Journal of Management Studies, 47*(3), 551–580. https://doi.org/10.1111/j.1467-6486.2010.00908.x

McKinsey & Company. (2023, June 14). *The economic potential of generative AI: The next productivity frontier*. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier

McKinsey & Company. (2024, May 30). *The state of AI in early 2024: Gen AI adoption spikes and starts to generate value.* https://www.mckinsey.com/~/media/mckinsey/business%20functions/quantumblack/our%20insights/the%20state%20of%20ai/2024/the-state-of-ai-in-early-2024-final.pdf

Mortenson, M. J., Doherty, N. F., & Robinson, S. (2015). Operational research from Taylorism to Terabytes: A research agenda for the analytics age. *European Journal of Operational Research, 241*(3), 583–595. https://doi.org/10.1016/j.ejor.2014.08.029

Nanli, Z., Ping, Z., Weiguo, L., & Meng, C. (2012). *Sentiment analysis: A literature review* [Paper presentation]. 2012 International Symposium on Management of Technology (ISMOT), Hangzhou, China. https://doi.org/10.1109/ISMOT.2012.6679538

Phillips, J., & Klein, J. D. (2023). Change management: From theory to practice. *TechTrends, 67*(1), 189–197. https://doi.org/10.1007/s11528-022-00775-0

Poudel, D. (2019). Making sense or betting on the future?: Identifying antenarratives of AI projects in a large financial organization. *Electronic Journal of Business Ethics and Organization Studies, 2*(2), 20–33. http://ejbo.jyu.fi/pdf/ejbo_vol24_no2_pages_20-33.pdf

Prosci Inc. (2016). *The Prosci ADKAR model*. Prosci. https://empower.prosci.com/en-us/the-prosci-adkar-model-ebook

Raelin, J. A. (2016). Imagine there are no leaders: Reframing leadership as collaborative agency. *Leadership, 12*(2), 131–158. https://doi.org/10.1177/1742715014558076

Rafferty, A. E., Jimmieson, N. L., & Armenakis, A. A. (2013). Change readiness: A multilevel review. *Journal of Management*, *39*(1), 110–135. https://doi.org/10.1177/0149206312457417

Ravitch, S. M., & Carl, N. M. (2019). *Qualitative research: Bridging the conceptual, theoretical, and methodological*. SAGE Publications.

Roy, D., Srivastava, R., Jat, M., Karaca, & M. S. (2022). A complete overview of analytics techniques: Descriptive, predictive, and prescriptive. In P. M. Jeyanthi, T. Choudhury, D. Hack-Polay, T. P. Singh, & S. Abujar (Eds.), *Decision intelligence analytics and the implementation of strategic business management* (pp. 15–30). Springer, Cham. https://doi.org/10.1007/978-3-030-82763-2_2

Silver, N. (2020). *The signal and the noise: The art and science of prediction*. Penguin Books.

Steigenberger, N. (2015). Emotions in sensemaking: A change management perspective. *Journal of Organizational Change Management, 28*(3), 432–451. https://doi.org/10.1108/JOCM-05-2014-0095

Vanderbilt University. (2023). *Academic affairs guidance for artificial intelligence (AI) tools*. https://cdn.vanderbilt.edu/vu-URL/wp-content/uploads/sites/439/2023/11/29200845/Academic-Affairs-Guidance-for-Artificial-Intelligence-Nov-29-2023.pdf

Waterman, R. H. (1982). The seven elements of strategic fit*.* *The Journal of Business Strategy, 2*(3), 69.

Weick, K. E. (1993). The collapse of sensemaking in organizations: The Mann Gulch disaster. *Administrative Science Quarterly*, 38(4), 628-652. Sage Publications. https://www.jstor.org/stable/2393339

Weick, K. E. (1995). *Sensemaking in organizations*. Sage Publications.

Weick, K. E., Sutcliffe, K. M., & Obstfeld, D. (2005). Organizing and the process of sensemaking. *Organization Science, 16*(4), 409–421. https://doi.org/10.1287/orsc.1050.0133

Wijayati, D. T., Rayman, Z., Fahrullah, A., Rahman, M. F. W., Arifah, I. D. C., & Kautsar, A. (2022). A study of artificial intelligence on employee performance and work engagement: A moderating role of change leadership. *International Journal of Manpower*, *43*(2), 486–512.

Appendix A: Interview Schedule

Table A1

Interviews

	Lead or End User	Unit/Title (altered slightly to generalize)	Interview (virtual via Microsoft Teams)
1	Lead	Enterprise Data Office Lead	February 26, 2024
2	Lead	Enterprise Data Office Director	February 27, 2024
3	End User	Data Insights Lead	February 27, 2024
4	Lead	Enterprise Data Office Vice President	February 27, 204
5	End User	Financial Analysis Manager	March 4, 2024
6	End User	Financial Analysis Manager	March 4, 2024
7	Lead	Global Business Insights Director	March 4, 2024
8	End User	Global Business Insights Manager	March 5, 2024
9	Lead	Enterprise Data Office Lead	March 6, 2024
10	End User	Financial Analysis Senior Manager	March 7, 2024
11	End User	Financial Analysis Manager	March 12, 2024
12	Lead	Global Business Insights Lead	March 12, 2024
13	End User	Financial Planning and Analysis Lead	March 18, 2024
14	End User	Global Business Insights Senior Manager	March 18, 2024
15	Lead	Delivery Lead	March 19, 2024
16	End User	Financial Planning and Analysis Lead	March 20, 2024
17	Lead	Financial Analysis Director	March 20, 2024
18	Lead	Finance Vice President	March 26, 2024
19	Lead	Enterprise Data Office Manager	March 26, 2024
20	Lead	International Markets Vice President	March 28, 12024
21	Lead	Enterprise Data Office Director	April 9, 2024

Field Observations
The Company Data Fest: April 30, 2024
Company Headquarters, Midwest State

Appendix B: Interview Protocol

PROTOCOL FOR LEADERS

SECTION 1: Change Management; Change Readiness; ADKAR Change Model (Hiatt, 2006)

1. Can you tell me about your role and in the context of your role, how you define analytics?
2. On a scale of 1 to 10, how critical do you believe data literacy is for your team's success, and why?
3. In your team, do you make a distinction in conversations between descriptive and predictive analytics?
4. Can you identify specific areas of your daily tasks that could benefit from enhanced data analysis? (What is the excitement for your team around this?)
5. If possible, could you estimate the percentage improvement in efficiency or productivity you might achieve by incorporating more data analysis into your work?
6. What might change for you with more advanced analytics?
7. Please answer the degree to which your team:
    a. Is aware of the potential to utilize advanced analytics?
    b. Desires to adopt and explore advanced analytics?
    c. Has knowledge to apply and utilize advanced analytics?
    d. Has the skills and abilities they need to use advanced analytics?
    e. Are regularly using advanced analytics and measuring impact?

SECTION 2: Sensemaking; Antenarratives (Poudel, 2019)

1. How do you actively promote the adoption of an analytics-driven mindset among your team members?
2. Can you describe the strategies or methods you use with team members to leverage advanced data analytics and shift that mindset? How do you talk about it?
3. What kinds of stories or conversations do people tell about using advanced analytics?
4. Would you say the stories being told in this kind of area are generally negative or generally positive?

SECTION 3: Investment in Learning

1. Do you prefer to learn analytics skills to conduct your own analysis, have guided assistance, or delegate analytics tasks entirely? Why?
2. What do you think the main obstacles are that your team faces in adopting data analytics technologies and practices?
3. What amount of time per month would you or your team be willing to dedicate to enhancing your data literacy and analytics skills?
4. What learning formats (e.g., newsletters, dashboards, workshops, formal training) do you believe would be most effective for your team to enhance data analytics capabilities?
5. Logistical question: Would you devote funding each year if you could quantify results by better data understanding?

PROTOCOL FOR END USERS

SECTION 1: Change Management; Change Readiness; ADKAR Change Model (Hiatt, 2006)

1. How do you define 'analytics' within the context of your role?
2. On a scale of 1 to 10, how critical do you believe data literacy is for your success, and why?
3. Do you make a distinction between descriptive and predictive analytics in your work?
4. Can you identify specific areas of your daily tasks that could benefit from enhanced data analysis?
5. If possible, could you estimate the percentage improvement in efficiency or productivity you might achieve by incorporating more data analysis into your work?
6. What might change for you with more advanced analytics?
7. To what degree do you feel like you have:
    a. Awareness of the potential to utilize advanced analytics?
    b. Desire to adopt and explore advanced analytics?
    c. Knowledge to apply and utilize advanced analytics?
    d. Skills and abilities to use advanced analytics?
    e. Reinforcement/Positive feedback from leaders to use advanced analytics?

SECTION 2: Sensemaking; Antenarratives (Poudel, 2019)

1. Could you walk us through how new technologies have typically been introduced and used within your team?
2. Will you describe a situation where you felt supported or guided in understanding and adopting a new analytical tool or method?

3. Have there been any instances of confusion or resistance among yourself or team members when introducing new technologies? In what ways were these challenges addressed?
4. What specific actions or efforts from your leaders have been most effective in helping you grasp the functionalities and benefits of data analytics and methods?
5. Would you say the stories being told in this kind of area are generally negative or generally positive?

SECTION 3: Investment in Learning

1. Do you prefer to learn analytics skills to conduct your own analysis, have guided assistance, or delegate analytics tasks entirely? Why?
2. What do you think the main obstacles are that you face in adopting data analytics technologies and practices?
3. What amount of time per month would you be willing to dedicate to enhancing your data literacy and analytics skills?
4. What learning formats (e.g., newsletters, dashboards, workshops, formal training) do you believe would be most effective for your team to enhance data analytics capabilities?

Appendix C: Use of AI in the Project

Just as the industry seeks to embrace artificial intelligence-powered tools for a competitive edge, doctoral researchers have various tools available that both provide efficiencies and raise issues of responsible and ethical use. In 2024, new tools are rapidly emerging, and artificial intelligence (AI) is increasingly embedded in long-used tools, requiring careful examination of all online research tools with intentional and transparent use.

The act of doctoral-level research is intended to add to societal knowledge while training the doctoral student in scholarship, creativity, and inquiry (Bargar & Duncan, 1982). Introducing the Leadership and Learning in Organizations program at Vanderbilt University, program director Dr. Eve Rifkin encouraged students to think of themselves as entering an academic conversation mid-stream and contributing to the scholarship and practice moving forward. AI-powered research tools can enhance the quality of doctoral research, providing access to a greater body of research (Christou, 2023) more rapidly. However, scholars urge that the desire to speed up research using AI should be balanced with the demands for critical analysis and creativity in solid investigations (Chubb et al., 2022).

For this capstone project focused on AI adoption in a large company, we sought to embrace and explore AI in the research process. With a philosophical approach that AI can and should be a partner in the research process, we agreed that all submitted work would be transparent in using AI and address ethical considerations (see Table C1). We fully agree and comply with Vanderbilt University (2023) Academic Affairs Policy, effective January 2024, that we are “responsible for its accuracy, impact, and compliance with relevant laws and policies” (para. 1).

Emerging research details ethical concerns including privacy and security, bias and fairness, trust and reliability, transparency, and human-AI interactions (Hastuti & Syafruddin, 2023; Kamila & Jasrotia, 2023). Responsible use and ethical considerations of using AI-powered tools in this project include:

- Originality and intellectual property ownership: We understand the scholar's responsibility to add original thinking to academic discourse. AI tools can quickly generate, edit, and refine text. We deliberately wrote all drafts before consulting AI tools and then carefully edited them to maintain original contribution to the field.
- Reliability and accuracy: AI tools can quickly generate abstracts and references but may cite ideas out of context. We reviewed all articles cited in this project and downloaded them to an available repository.
- Awareness of potential bias: Scholars are appropriately concerned with how AI can perpetuate and exaggerate bias (Hastuti & Syafruddin, 2023; Kamila & Jasrotia, 2023). Since AI tools are trained on historical data, systemic bias may be deeply embedded. We maintained vigilance in questioning potential bias and sought counsel throughout the project when selecting and using AI tools for research.

An ethical consideration for researchers focuses on the opaqueness of AI algorithms, resulting in a lack of trust of outputs (Kamila & Jasrotia, 2023). We questioned AI-recommended articles and research summaries and chose multiple tools and methods to seek research. Varied queries resulted in a broad range of literature that could be cross-referenced for applicability to the project. Related, we opted for redundancy of AI tools for tasks like recording interviews, as we found that different tools provided different types of summaries and insights.

Table C1

Artificial Intelligence Tools Utilized in this Project

Tool	Description
Research	
Humata https://app.humata.ai/	Humata AI summarizes and analyzes PDF documents. It uses natural language processing (NLP) to analyze PDFs inputted into the database. The tool will summarize, answer queries, and provide quick access to reference points in given articles. The authors cross-checked all references suggested in Humata, returning to the original articles for context.
Elicit https://elicit.com/	Elicit acts like a research assistant, searching Semantic Scholar based on queries and then analyzing selected articles for themes, key ideas, and summaries. The technology is Generative Pre-trained Transformer 3 (GPT3) to search and summarize.

	The authors cross-referenced articles identified by Elicit with the Vanderbilt library and downloaded all PDFs for original review.
Google Scholar, Google Search, and Gemini https://scholar.google.com/ https://www.google.com/ https://gemini.google.com/	Recommended by the Vanderbilt librarian, Google Scholar searches academic and scholarly sources to index and organize literature based on queries. Using machine learning, the Google tools rapidly provide a breath of information. Specific and sophisticated queries help narrow the search for the most relevant sources. Introduced in early 2024, Google Gemini is a family of AI large language models (LLMs) that can assist in a wide range of research tasks, including identifying research, summarizing ideas, refining text, and more. The authors cross-referenced articles identified by Google Scholar and Gemini with the Vanderbilt library and downloaded all PDFs for original review.
Amazon https://www.amazon.com/	Amazon uses AI and machine learning models in a variety of ways to sell products and assist customers. For research

	purposes, Amazon suggested related books on the identified topic for consideration.
Writing and Idea Generation	
Grammarly https://www.grammarly.com/	Grammarly assists the writing process with grammatical corrections and suggestions for rephrasing for clarity. The technology combines machine learning with natural language processing approaches.
Chat GPT https://chat.openai.com/ Doctoral Assistant GPT	ChatGPT, or Chat Generative Pre-Trained Transformer, is an AI chatbot that uses machine learning to process and respond to inquiries. Introduced widely in 2023, the tool may be used in research for a range of tasks. We used a premium version most often for idea generation. Accuracy and bias are known issues with ChatGPT that were considered with use.
Data Collection and Analysis	
Fathom https://fathom.video/	Fathom records, transcribes, highlights, and summarizes meetings. Fathom reports that it uses a closed API developed in partnership with OpenAI, Microsoft, and Anthropic and combined with proprietary models. Fathom

	video recording was selected for ease of use with Microsoft Teams and security guarantees.
Otter.ai https://otter.ai/	Otter.ai transcribes audio from different sources, including recorded meetings, live conversations, and audio files. Otter.ai uses machine learning and natural language processing to transcribe audio to text. File summaries and highlights are available. Otter.ai was used as a back-up to Fathom.
MAXQDA https://www.maxqda.com/	MAXQDA is a software package for qualitative and mixed methods research. Interview transcripts and recordings may be uploaded and MAXQDA tools support coding, categorization, and text analysis. This tool was recommended and selected for the AI integration with AI assist that supports analysis and summarization. Researchers used a student version with AI assist.
Other key tools used were Microsoft Teams and Google Drive. While these tools incorporate AI, that functionality was not intentionally used in this project.	