An Examination of The Path to Prescriptive Analytics

by

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ABSTRACT

The difficulty of demonstrating a significant return on investment from the use of advanced data analytics has led to a lack of utilization of this tool. The most likely explanation for this phenomenon is the difficulty of incorporating non-financial metrics in the higher levels of analysis that are fully salient and derived in a manner that can be understood and trusted by organizational leaders. Another challenge that has confounded the use of advanced analytics by the leadership of organizations is the widely accepted belief that models are oftentimes developed with an insufficient number of variables that are expected to have an impact, which inhibits extrapolation of results for use in real-world decision making. This research identifies factors that contribute to the underutilization of analytics models in managerial decisions by leadership of the produce industry, and explores a variety of potential tools including descriptive analytics and dashboards that are able to provide predictive, prescriptive, and more advanced cognitive methods of decision making for use by organizational leadership. By understanding the disconnect between availability of the advanced data analysis tools and use of such tools by organizational leadership, this research assists in identifying the programs and resources that should be developed and presented as opportunities for support in the industrial decision-making process.

This dissertation explores why managers within the produce industry underutilize higher levels of data analytics and whether it is possible to increase their levels of cognitive comfort. It shows that by providing leadership with digestible and rudimentary business experiments, they become more comfortable with more complex data analytics and then are better able to utilize dashboards and other tools within their decision-making

models. As experiments are explained to managers, they become as comfortable with conducting experiments as they are with dashboards, thus becoming comfortable with evaluating their benefits.

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1. INTRODUCTION

1.1. The Problem

New technologies are emerging to integrate data analytics into the workplace. As big data is becoming more readily available and comprehensive than ever before, it is imperative that businesses and executives understand and utilize this abundance of data. However, research demonstrates that out of 7,000 exabytes of data stored worldwide in 2014, only 0.5% was analyzed (Davenport, 2014). Most organizations have only started employing pivot tables and dashboards and these do not constitute next level data analytics, thus revealing an overwhelming lack of big data implementation. As shown in

Table 1, most firms have not progressed beyond the level of descriptive analytics (Glassman, Shao, & St. Louis, 2019).

Data analytics is the process of applying advanced analytics techniques to data as to improve organizational performance (Rozados & Tjahjono, 2014). Businesses across all industries understand the value of data analytics, resulting in an increasing amount of readily available data sources and applications, including dashboards and pivot tables. Modern digital technologies that apply this scientific approach to business have generated information systems that assist the collecting, analyzing, and organizing of data in a more cost effective and timely manner. This dissertation focuses on these functionalities as they relate to supply chain management (SCM). The critical inference driving the investigation is that the availability of resources and technologies pertaining to analytics should result in more sophisticated analyses. However, this adoption has not been observed, and the lack of adoption is consistent across multiple industries. Research into

SCM can articulate how this functional area, of which the fundamental application is production and distribution, does not maximize the possible returns from using data analytics. Research into business intelligence has distinguished a common hierarchy of analytics that differentiates between five ascending levels as shown in Figure 1. The relevant areas that will be focused on are defined as descriptive analytics, predictive analytics, and prescriptive analytics. Descriptive analytics is involved in monitoring performance and understanding the driving forces. Predictive analytics relies on past data to predict future actions, behaviors, or outcomes. Prescriptive analytics provides insights into potential consequences that result from different actions by outlining key cause-and-effect relationships (Blum, Goldfarb, & Lederman, 2015). Interestingly, Shao and St. Louis (2019) show that the majority of firms in their sample of 15 firms may not have progressed beyond the level of descriptive analytics (Shao & St. Louis, 2019). In their particular sample, only 44% of the firms had progressed beyond descriptive analytics (Glassman, Shao, & St. Louis, 2019).

Table 1: Assessment of the Level of Data Analytics via Interviews with CPOs (Source: (Glassman, Shao, & St. Louis , 2019))

Level	# of Firms
Cognition (L5)	1
Prescription (L4)	0
Prediction (L3)	5
Description (L2)	9
Collection (L1)	0

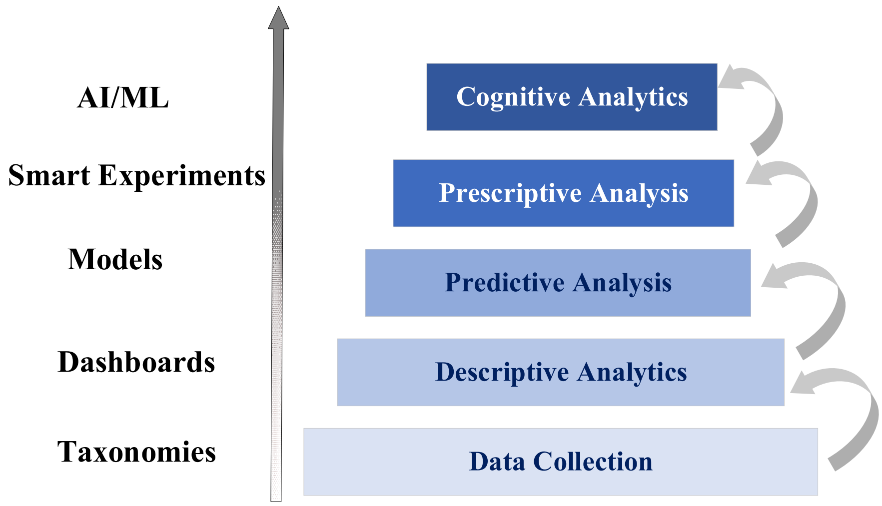

Figure 1 : Analytics Hierarchy (Source: (Glassman, Shao, & St. Louis, 2019)

1.2. What is Data Analytics?

Data analytics is defined as the application of advanced techniques to extract actionable results from data (Rozados & Tjahjono, 2014). Data analytics can also be defined as the application of mathematical methods to gain information from the data, which is then used to optimize decision-making processes (Baum, Laroque, Oeser, Skoogh, & Subramaniyan, 2018). Data analytics refers to the qualitative and quantitative techniques and processes used to enhance productivity and business gain (Sivarajah, Kamal, Irani, & Weerakkody, 2017). Data is extracted and categorized to identify and analyze behaviors in terms of patterns and techniques that vary according to organizational requirements (Gandomi & Haider, 2015). Thus, to better understand and classify the basics of data analytics, it's contexts within big data must be defined.

Big data consists of three essential characteristics: volume, velocity, and variety. Volume accounts for the amount of data, velocity refers to the rate at which the data is recorded and processed, and variety explains the differences in terms of context and structure within the data (Baum, Laroque, Oeser, Skoogh, & Subramaniyan, 2018). Big data attempts to be "exhaustive in breadth and depth and more fine-grained in resolution than traditional data, often indexing individual persons or objects instead of aggregating data at the group level" (Kitchin, 2014). Thus, big data analytics can be defined as the statistical modeling process that analyzes large, diverse, and dynamic data sets (Müller, Junglas, Brocke, & Debortoli, 2016).

Big data analytics and its applications within SCM assists in analyzing useful data by identifying patterns and techniques relative to the acquisition and distribution of goods and services. These technologies include, but are not limited to, the use of electronic data exchange, radio frequency identification, bar codes, electronic commerce, decision support systems, enterprise resource planning packages, and the World Wide Web (Varma & Khan, 2015). Ultimately, big data analytics within SCM is best utilized when incorporating advanced analytics techniques in combination with datasets that require information technology tools (Rozados & Tjahjono, 2014).

1.3. Analytics Hierarchy of Needs

Maslow's hierarchy of needs is a five-tier model of human needs and is derived from the field of psychology. This hierarchy aims to simplify the complex set of goals that humans have evolved to fulfill over time. Maslow formulated a positive theory of motivation that satisfies theoretical demands and conforms to known facts through clinical, observational, and experimental studies (Maslow, 1943). Ultimately, he concluded that the most basic of all needs are our physiological needs. For example, an individual lacking food, safety, love, and esteem would most likely assert hunger and the drive to obtain food as their strongest need. Once these physiological needs are met, higher needs emerge and dominate the organism until these needs are met, and then new and higher needs emerge, and so on, thus outlining how the hierarchical model is organized in terms of relative prepotency.

The model is displayed on a pyramid graphic to organize the goals in a way that demonstrates how each level must be met before moving onto the next level. This was later modified to state that the level did not need be completed in its entirety to progress (Maslow, 1943). However, meeting all of the goals on each level before moving upward has been commonly recommended by researchers to optimize movement up the hierarchy.

The hierarchical model in Figure 1 demonstrates how data analytics can be used to its maximum potential. The initial implementation of data analytics starts at the first level, which is known as *data collection*. Taxonomies are a primary method of organizing the initial collection of data, as taxonomies can optimize the data quality and navigation processes. In this era of big data, cleaning massive amounts of heterogeneous, structured, or unstructured data remains imperative (Siddiqa, et al., 2017). To satisfy this fundamental level, data engineers and data architects must define what data is collected, ensure that the pipeline is working, and monitor the quality of the data to utilize (Guiterrez, 2016). Similar to a faucet with old and rusty water (big data), a filter must be attached in order to clean the water and ensure its drinkability (fulfilled data collection) (Shealy, 2016).

The next level is *descriptive analytics.* These analytics develop a summary of the data's history in preparation for further analysis and cannot be conducted without first fulfilling data collection. Descriptive analytics consists of analytical applications based on past and present data, and these applications serve to describe and better understand situations (Baum, Laroque, Oeser, Skoogh, & Subramaniyan, 2018). Descriptive analytics also offers the organization useful information about current events by using dashboard software, which simplifies complex data to improve business intelligence. This level of analytics involves asking questions and generating straightforward numerical answers.

Once reliable data has been established at level one, technologies such as dashboards and pivot tables are used to summarize the data. These features enable stakeholders in organizations to evaluate what guides optimal performance, and the pivot tables help to understand what drives optimal performance. These technologies are then regularly monitored to follow trends and usage for decision-making purposes (Shealy, 2016). This level of analytics can be fulfilled by demonstrating the ability to monitor performance and establish what is driving that performance. Most firms currently function at the level of descriptive analytics.

The next level in the model involves *predictive analytics*, which focus on current data to make calculated predictions. However, in order to progress to this predictive level, data scientists with more specialized skills that are more specialized are employed to build models that are then implemented by software engineers. Some techniques incorporated at this level are data mining, statistics, and predictive modeling that seek to determine the probability of an outcome. A foundation built by an effective data ingestion system and a concrete understanding of the data is necessary when fulfilling this level of data analytics (Shealy, 2016).

The company's *prescriptive analytics* is related to both descriptive and predictive analytics, but distinguished in that prescriptive analytics calculates the best course of action based on analytics acquired in the levels beneath it. Not only do these analytics tell us what and when things will happen, but more importantly, why they will happen. Predictive analytics would forecast that only a few people will buy the product, whereas prescriptive analytics indicate why they will not buy the product (Bull, Centurion, Kearns, Kelso, & Viswanathan, 2019). Prescriptive analytics should integrate technologies and software applications designed to conduct qualitative and quantitative research into relevant data experiments (Anderson & Simester, 2011).

The highest integration of data analytics results in the *embedded* automation of tools such as machine learning and artificial intelligence (A.I.). This technology integrates the entire analytical process through the machine making corrections and learning from its own experience. A.I. and machine learning have made significant technological advancements that initially were not expected to be reached for another ten years (Shealy, 2016). Per Maslow's insight into a generalized hierarchy of needs in 1943, the highest level should encompass and fulfill each level within the hierarchical model. Maslow's rules for the hierarchy apply to this model.

Ideally, an organization moving up the hierarchal model would begin by cleaning the data, creating a pipeline, and monitoring the data during the first level of data collection. The organization would then implement dashboards and pivot tables, enabling it to follow usage and trends within the data, ultimately demonstrating the ability to monitor their performance and its driving forces while in the level of descriptive analytics. Once this level has been fulfilled, more sophisticated techniques, such as data mining, statistics, and predictive modeling can be implemented to demonstrate the probability of certain outcomes. Building these models at the predictive level requires the organization to hire data scientists and software engineers with advanced skills and knowledge. The organization will then utilize these applications to determine the best course of action by extracting relevant insights into why things will or will not happen. Then, they can begin using A.I. and machine learning to automate their decision-making processes. This embedded level of data analytics can only be reached once the organization has fulfilled every level leading up to the highest level within the model.

1.4. Pilot Survey Results

Experts analyzing data integration agree that organizations are unconscious of their lack of progression. Davenport explains that businesses are not informed of these data barriers and that they lack experience with analytics (Davenport, 2014). The analytical process comprised of dissecting past data is nothing short of complex. Past research demonstrates that most firms do not have the technical skills involved to incorporate advanced analytical programs. Our pilot study reflects these conclusions, which account for the observed lack of progression.

The pilot study consisted of 15 firms and their respective CPOs. The interviews were administered by a Center for Advanced Procurement Strategy (CAPS) research team (Shao & St. Louis, 2019). The study consisted of an initial insight survey, followed by in-depth interviews with 15 CPOs and other business managers.

The transcripts from the interviews were studied and codified to the hierarchical model listed above. Most organizations appear not to have progressed past the level of descriptive analytics (Glassman, Shao, & St. Louis, 2019). To be exact, out of fifteen firms, nine of the firms were in the descriptive analytics level, five were in the predictive analytics level, and only one reached the highest level of data analytics.

Informed businesses desire to move rapidly within the hierarchical model to achieve optimal self-service analytics; however, they lack the ability to progress. Past research has shown that companies cannot jump to the highest level within the hierarchical model without mastering the level immediately below. Without encompassing the competencies involved at each fundamental level, higher stages may initially work but eventually will crumble (Shealy, 2016). The CAPS investigation identifies these obstacles and how businesses can overcome them (Shao & St. Louis, 2019).

1.5. The Roadblocks

Multiple issues have been identified pertaining to the descriptive level of data analytics and the reasoning behind its stagnant nature within the SCM industry. The quality of data collected in the first level must be at a high level before attempting to analyze it. Deficits in data architecture, such as the level of granularity, were identified.

Faulty data results from the acquisition of convenient, low granular level data. To move to the next level of predictive analytics, data must be collected, cleaned, integrated, and governed. Businesses are moving onto this level by analyzing inaccurate and low-level data, which is a primary reason why most cannot move up the hierarchy.

The basic principle established by Maslow was the concept of no shortcuts (Maslow, 1943). Furthermore, other hierarchies began to emerge relating to the needs within an organization, embedded in Maslow's basic principle. If a business does not have an adequate collection or understanding of their initial data collection, they are unable to move on to the next level. Procedures involved in faulty data governance can affect how the data is integrated and stored, and it results in the lack of analysis.

Exploration into how much of this low-level data has been retained and integrated within the industry was further investigated. The investigation began with the executive responsible for improving business performance by contracting services or managing the purchase of supplies, equipment, and other materials. This individual is the head of procurement, also known as the Chief Procurement Officer (CPO). CPOs provide structure within their organization and specifically manage and organize teams involved in gathering data analytics local to procurement (i.e., how something is strategically and operationally obtained within a business).

The next level of predictive analytics utilizes models from past data to make predictions on possible actions, behaviors, and outcomes. Once CPOs understand this level, they can move to the level of prescriptive analytics. Prescriptive analytics differs from predictive analytics because it aims to understand the factors that determined the predicted outcome. CPOs or other managers have been found to not be comfortable with these two levels of analytics and often associate predictive analytics with complicated models. Davenport claims that, due to lack of experience, product managers are not comfortable with developing and launching data products (Davenport, 2014).

1.6. Research Question and Approach

The CPOs interviewed within the pilot study emphasized the importance of building a data analytics team. To better understand the process of structuring a data analytics team, the types of individuals necessary for the CPOs to hire and retain must be elaborated on. First, we need data scientists; these scientists incorporate raw data to develop models that are then implemented in specific business contexts. Next, the team needs software engineers who have experience in architecture, infrastructure, and distributed programming. Then, to understand the processes related to procurement and converting data analytics results into action, the team should utilize procurement domain experts. Lastly, a team of data analysts should have a manager who is able to utilize data analytics to forecast, orchestrate how these analytics are used, and guide these results to improve the overall performance of the business.

From these interviews, the CPOs identified two problems. The first problem related to deficits within the structure of their data analytics team. They had hired managers who were not interacting appropriately with the rest of the team. The second problem was that managers also viewed the predictive level as too complex, resulting in the inability to move out of the descriptive level within the hierarchical model.

The approach is to utilize this information to educate managers within data analytics teams to conduct smart business experiments instead of simple business experiments. Simple business experiments are usually conducted because it is easier for them to draw conclusions. Anderson and Simester (2011) offer seven rules for conducting smart business experiments that will achieve the level of prescriptive analytics and beyond. These rules involve focusing on the individuals within the team, keeping it simple, proof of concept, slicing the data, thinking outside the box, measuring everything, and seeking natural experiments. Managers should utilize these rules for their smart experiments and ask for help solving a problem, rather than asking for data.

Our previous case study interviewed 15 CPOs to determine the current status of organizations with respect to the data analytics hierarchy. The study identifies the roadblocks that organizations typically encountered as they attempt to move from descriptive to predictive to prescriptive analytics and the practices that companies have found to be the most effective for overcoming those roadblocks (Glassman, Shao, & St. Louis, 2019).

These issues identified within SCM motivated two fundamental questions driving my new research investigation. The questions are: 1) Why don't organizations create a strategic advantage by utilizing predictive and prescriptive methodologies?; and 2) How can the results of predictive and prescriptive analytics be made more salient?

Specifically, this study explores why managers within the produce industry underutilize higher levels of data analysis and whether it is possible to increase their levels of cognitive comfort. This study also hopes to show that by providing leadership with digestible and rudimentary business experiments, they become more comfortable with more complex data analytics and then are better able to utilize dashboards and other tools within their decision-making models. As experiments are explained to managers, they become as comfortable with conducting experiments as they are with dashboards, thus becoming comfortable with evaluating their benefits.

In the remainder of the dissertation I will conduct a literature review to link the relevant constructs and theories to investigate these phenomena. I will then develop an appropriate methodology to investigate this and conduct the study.

2. LITERATURE REVIEW

Much has been written that can further the understanding of the obstacles of utilizing sophisticated analytics. In the search for the cause of these obstacles, the literature can be divided into two levels of analysis that together provide a cohesive explanation of the problem. The first level of analysis is the organizational structures for data management. The most relevant to investigate are social technical systems theory, saliency, change management, and data architectures.

Having the right systems in place is only the first step in increasing the data analytics competency of an organization. An organization could have the best systems for analytics available but if the end users do not trust and utilize them, they will be wasted. The knowledge workers' view and trust of the organization's data is also very important. To investigate why users are underutilizing their information resources, it is necessary to understand how the psychological factors of saliency, trust and believability of data, and technology acceptance factor into this.

2.1. Social Technical Systems Theory

The social technical systems theory (STS) is comprised of interactions between the following sub-systems; structure, task, technology, and people. Trist (Trist E. , 1981) and Baxter and Sommerville (Baxter & Sommerville, 2011) identify a limit to the productivity increase that can occur within a given technology in the absence of cultural change. There is a limit to the productivity increase that can occur within a given culture in the absence of technology change. To improve the performance of an organization, the 'social' and 'technical' components must be brought together as interdependent parts of a socio-technical system, and they must change simultaneously. This is illustrated in Figure 2.

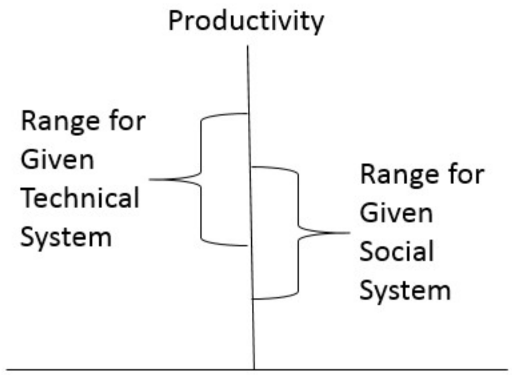

Figure 2: Interaction of Social and Technical Systems (Shao & St. Louis, 2019)

All organizations that employ people with capabilities who work toward goals, follow processes, use technology, operate within a physical infrastructure, and share cultural assumptions, can benefit from this theory. Despite the widespread value derived from this theory throughout multiple organizations, STS is not widely practiced (Baxter & Sommerville, 2011).

The SCM industry might view the STS theory as a potential onset to the problems identified in the introduction. Specifically, cohesion research has identified a range of issues that are addressed by having leadership internal to a group or team (Siebold, 1991). Siebold also suggests that the ability of each team member to perform their given function is not the only predictor of effectiveness within a group, thus validating the interdependent nature of STS and outlining how organizations should not hold a single employee accountable for deficiencies within business practices.

Research on adapting the STS theory within business practices has identified two options for dealing with environmental factors. First, the external complexity is met by increasing the internal complexity. This approach can lead to new organizational functions, which strategically react better to external developments (Sitter, Hertog, & Dankbaar, 1997). Internal complexities can increase by implementing staff functions or enlarging staff functions already in place and/or investing in vertical information systems. Staff functions that promote interpersonal trust have been identified as an "important variable for effective management and the success of the organization" (Schraeder, Self, Jordan, & Portis, 2014, p. 50).

In contrast, Sitter, Hertog and Dankbaar (1997) determined that an alternative option is to deal with external complexity by 'reducing' internal control and coordination needs (Sitter, Hertog, & Dankbaar, 1997). This can be accomplished by creating "self-containing units and lateral groups" (Galbraith, 1974, p. 96). Its primary approach focuses on the work process itself by integrating more thinking and doing tasks, which results in less support from indirect staff, less bureaucracy, and better jobs (Sitter, Hertog, & Dankbaar, 1997).

Shapiro (2017) cautions that big data and dashboards may mislead managers. These cautions center around the choice of what information to present in a dashboard, being careful not to equate quantitative with objective, and being careful not to misattribute causality. Most importantly, Shapiro notes that there is no substitute for applying critical thinking to the outputs of analytics. In a similar vein, Blum, Goldfarb, and Lederman (Blum, Goldfarb, & Lederman, 2015) point out that closing the gap between the promise and reality of data analytics requires certain steps. These include the following: 1) focusing on the why and how of customer behavior, rather than the who, what, and which; 2) understanding the processes that generate the data; and 3) applying critical thinking to determine what is valid evidence and what is relevant evidence. They argue that it is not possible to move from descriptive to predictive to prescriptive analytics without following these steps.

STS theory views the experience of humans in systems and the systems' overall performance as one unit. Trist and Bamforth (Trist & Bamforth, 1951) identify the importance of social tasks when integrating STS. During their experiments, they determined that the key advantage came from placing the responsibility on a single and small face-to-face group. This group will accept all experiences relating to operations within their organization. Developing this group will provide these tasks with "total significance and dynamic closure" for each member (Trist & Bamforth, 1951, p. 6). This process offers more meaning to social tasks amongst group members, resulting in more productivity. It is important to remember that technology serves humans, instead of humans serving technology. Examining relative issues through the lens of STS theory is one way that organizations within SCM can identify the onset of inadequate data usage. Placing the full responsibility on an executive or management level employee might offer insight as to why organizations often do not progress beyond the descriptive level of analytics.

Past research helps us identify why STS has not been widely adapted, which is one reason firms may remain at the descriptive analytics level. Siebold (Siebold, 1991) suggests that organizations are holding single employees accountable for regulation and leadership responsibilities when they should be placed on a group or in a team. Environmental issues are also discussed that account for an organization's inability to progress through the hierarchal model. Sitter, Hertog, and Dankbaar (Sitter, Hertog, & Dankbaar, 1997) proposed that increasing internal complexities by implementing staff functions would restore external complexities. They also identify that to implement STS, organizations must address external complexities by reducing internal control. Most notably, managers must be cautious regarding their use of dashboards and misattributing causality. STS integration can be accomplished by focusing on customer behavior, understanding the process through gathering data, and applying the evidence through critical thinking (Blum, Goldfarb, & Lederman, 2015). Ultimately, adapting STS and its relative functions may lead to firms progressing up the hierarchal model.

2.2. Saliency

Due to the evolution of cloud computing technologies, a significant advancement has been made in our ability to generate vast amounts of data. The challenges within this era of big data revolve around how to manage such voluminous amounts of data (Siddiqa, et al., 2017). Recent advancements in big data resulted in innovative techniques and technologies that assist in handling big data. However, research investigating these techniques and technologies is still being conducted. Numerous studies have explored big data and its saliency to business practices within SCM. Saliency is defined as the quality of something being particularly important and standing out amongst other things. Saliency within big data explains how users can explore and comprehend large amounts of information (Matzen, Haass, Divis, Wang, & Wilson, 2018). Exploration into big data outlines the need for strategic planning in order to capitalize on the saliency of the results from these analytics. This level of planning can only result from management that is fully educated and experienced with big data.

Research into big data is relatively new and is considered a multidisciplinary field. Big data refers to the different levels of analytics established from the hierarchical model. These analytics relate to business intelligence, where structured data transforms into unstructured, mobile, and sensor applications (Brinch, Stentoft, & Jensen, 2017). Therefore, the data is analyzed in a context-specific way to demonstrate actionable insights, which results in a competitive advantage (Fosso Wamba, Akter, Edwards, Chopin, & and Gnanzou, 2015). These insights can then be used to either support decision-making or become operationalized for automated decision-making.

It is important to note the distinction between big data and business analytics to better understand saliency. These distinctions are due to the technological aspects within big data and the prerequisite knowledge necessary to generate value. Information systems aim to help with data collection, data management, and data utilization with the common goal to increase business performance. These applications differ from those of business analytics in terms of volume, velocity, variety, veracity, and value (Brinch, Stentoft, & Jensen, 2017). Volume of big data relate to the substantial amount of data that is generated by machines, networks, and human interaction systems. Velocity relates to fast pace at which data transits in and between these systems. Big data veracity differentiates between biases and noise within the data that is stored and mined and whether it is meaningful (Banumathi & Aloysius, 2017). Value of big data relates to the ethics and the protection of the database and its subjective nature (Mohan, 2017). It is important to define big data to distinguish it from other relative constructs in an effort to increase its saliency. Another challenge embedded within big data is regional availability. Available data is generally smaller in rural areas compared to metropolitan cities, which influences the logistics and supply chain activities within these rural areas (Mohan, 2017).

One of the major challenges with incorporating big data involves its veracity. While analyzing a problem that big data aims to solve, one must analyze the abnormality of the data and determine its meaning for the problem (Banumathi & Aloysius, 2017). If the data is incorrect, outdated, or incomplete, time is wasted that could have been utilized toward innovation (Benabdellah, 2016).

Experts have concluded that the lack of strategic planning is a key factor resulting in inadequate data saliency. Brinch, Stentoft, and Jensen's (Brinch, Stentoft, & Jensen, 2017) findings demonstrate the important role that big data plays in the demand and supply strategy when planning. The incorporation of big data analytics has been instrumental to the underlying contributions to the non-financial metrics that involve sourcing, manufacturing, distributing, and marketing (Sanders, 2016). It is proposed that big data might assist various analytics procedures, which will result in more effective decisions for strategic and operational applications (Brinch, Stentoft, & Jensen, 2017), thus recognizing the saliency that big data theoretically identifies as a causal onset to the problems identified.

Research findings from big data experts ranked the areas of application pertaining to big data within SCM. Out of 39 applications, planning was ranked fourth. Experts concluded that, with regard to planning, big data can significantly influence techniques that improve forecasting and offer insight to end-user consumption for existing products (Brinch, Stentoft, & Jensen, 2017).

It has been theorized that inefficient knowledge of the saliency of big data might be due to the lack of experience managing it. Within large volumes of data, visibility is generally low because of a lack of expertise for analyzing big data (Mohan, 2017). In order to manage big data, a transparent IT-infrastructure must be in place that organizes structured data from unstructured data (Duan & Xiong, 2015). Through this infrastructure, techniques relating to data analytics are then applied. These techniques, as outlined by the hierarchy of needs, refer to machine learning, data mining, and visualization methods (Chen & Zhang, 2014). Without the knowledge discovery that develops through experience with data recording, data integration, data analysis, and data presentation, businesses may experience poor decision making.

The highest score (the most important) was the service processes extracted from big data. The responses from the experts demonstrated congruence with all eight statements. The statements regarding sourcing expressed that "big data will most likely be used as decision support for purchasing and information that can be utilized when negotiating with suppliers" (Brinch, Stentoft, & Jensen, 2017, p. 1355). Statements on manufacturing agree that big data has the greatest impact on organizational possibilities, outlines root causes for relative issues, and offer insight into the manufacturing processes.

These statements reveal the nature of big data and its service applications when deployed properly. The services will improve the identification of customer segments, gain insights from customers, adjust and/or develop service offerings, and direct marketing tactics (Brinch, Stentoft, & Jensen, 2017).

Given the saliency of big data and the current findings that outline the operational and strategic impacts, the paucity of research is due to the assessment of business value as it relates to data systems within a SCM framework. Businesses and experts have positive sentiments regarding big data. However, the business literature available is fragmented (Brinch, Stentoft, & Jensen, 2017). Existing literature validates the pervasiveness of big data but lacks empirical research that tests its applications. This demonstrates the need for more research into big data and its applications regarding SCM processes. The theoretical gap in the available research was a driving force behind my investigation. Management and executives responsible for understanding big data provide insights as to why most firms have not moved beyond the level of descriptive analytics.

2.3. Change Management

Management plays a key role in identifying why most firms have not progressed past the level of descriptive analytics. CPOs identified several obstacles that may account for the stagnant nature within the hierarchical model. First, management must recognize and understand the problems associated with not utilizing big data effectively. CPOs must be convinced of the compatibility and validity of the results that these technological innovations produce. Ultimately, they must believe that the proposed solutions that facilitate their organization moving up within the hierarchical model will be effective, thus affirming that the gain outweighs the risk.

A common pain point and one of the most frequent issues concerning management is the inadequate granularity of the data being stored, resulting in poor data governance. Many CPOs have not been significantly involved in governing the data needed to analyze spending costs and contract management. Liker and Choi (2004) stated that sharing vast amounts of information makes it more difficult to access the right information when necessary. Furthermore, management must start by acknowledging this problem and become more involved in the process of governing data.

Another hindrance amongst management was the inability to analyze relevant data and then integrate it. This is a result of not encompassing standardized processes and taxonomies to facilitate big data. A McKinsey Global Institute study estimated that about 1.5 million managers and analysts possess adequate decision-making skills based on analytical results (Manyika, et al., 2011). Managers with greater knowledge regarding technological innovation are significantly more likely to integrate these adoption policies (Ettlie, 1990). The foundation of this argument relates to overcoming the lack of knowledge of information systems, and leads to a greater likelihood of technological innovation. Consistent with Attewell's (1992) findings, lowering knowledge barriers involves the conceptualization of innovation diffusion. This concept goes beyond selling the importance of data analytics and places a greater emphasis on reducing knowledge hurdles that can be overcome by managing the process of changing organizations to better understand the source of quality data.

The third roadblock was a reluctance to progress within the hierarchical model. Most CPOs were not comfortable with advanced analytics and regard analytics as building complicated models instead of running simple experiments (Anderson & Simester, 2011). When businesses undertake uncertain tasks with complex information, management must implement various design strategies (Thong, 1999). If these strategies are not implemented, integrating these technological systems with vast amounts of information will be viewed as too complex, resulting in poor adoption. Schmarzo suggests that universities can assist by adequately preparing individuals for this business discipline, thus, transforming the education system to promote citizens of data science. (Schmarzo, 2013)

Similarly, research into the primary determinants for incorporating these information systems into businesses discovered that attitudes towards these systems were a determining variable. Relative advantage, compatibility, and complexity were the three essential attributes that influenced managements overall attitude on these technological innovations (Thong, 1999). Deficiency in any of these three attributes may result in a negative attitude toward adopting these technological systems. Analytics-based insights suggest that a major shift in attitudes is needed to accomplish a data-driven organizational culture (Pugna, Duţescu, & Stanila, 2019). People must be convinced that the data is trustworthy and facilitates informed recommendations instead of making decisions based on personal experience alone (Maguire, 2018).

Lastly, CPOs identified that support from top management and category managers was imperative (Shao & St. Louis, 2019). If members within an organization are not on the same page regarding the value of data analytics, this can result in serious cultural roadblocks. The main challenges that result in this identified lack of support are both the inspiration challenge and the unlearning challenge. One executive or employee cannot mandate the change alone. However, they can inspire those around them (Pugna, Duţescu, & Stanila, 2019). The unlearning challenge results from the senior executive's reluctance to unlearn routine assumptions concerning big data and technological systems.

Scientific and business research has outlined the positive impact from shifting to a data-driven organizational culture, with managers and executives primarily responsible for facilitating this shift. However, most organizations identified deficiencies in strong leadership relating to data and analytics (Pugna, Duţescu, & Stanila, 2019). Research on this topic demonstrated that even though 98.6% of executives report that their firms are in the process of embracing this type of corporate culture, only 32.4% are successful (Bean, 2018). A change in management skills is needed to incorporate new strategies and analytical models surrounding big data.

Concordant amongst research findings, management is substantially involved in factors that perpetuate the stagnant nature of businesses within SCM. These factors indicate why they have not progressed past the level of descriptive analytics. Research into identifying these roadblocks shows a common pain point: management's overall knowledge and attitude toward data innovation strategies and technological systems. When management is not involved in or knowledgeable about these systems, businesses may develop inadequate practices relating to data governance. Incorporating taxonomies and information systems with design strategies to facilitate big data can eliminate obstacles identified by CPOs. Strategies to overcome deficits in knowledge and experience surrounding big data must also be congruous with CPOs and top-level management. However, knowledge pertaining to these practices and the incorporation of data systems involve a shift that evokes positive attitudes towards them. CPOs and upper management must be convinced of the relative advantages that these systems and knowledge bring to the organization. CPOs must be convinced of the compatibility and validity from the results that these technological innovations produce. Ambivalent attitudes regarding the overall complexity within the data management culture must also shift. Once these problems have been acknowledged and solved, organizations will be able to integrate proposed solutions, resulting in higher levels of data analysis, thus moving past the descriptive level of analytics and onto predictive and prescriptive levels. Managers and executives must be convinced that the gain is worth the effort and greatly outweighs any relative risks associated with big data and the innovative strategies that govern these technological systems.

2.4. Data Analytics

In order to progress up the hierarchical model, organizations must understand and possess the characteristics for each level of data analytics. As outlined, the initial level involves data collection. The quality of data being analyzed cannot be greater than the quality of data collected. Data collection must encompass data cleaning, integration, governance, and retrieval procedures to move up to the descriptive level.

Descriptive level data analytics monitor key performance indicators (KPIs) through dashboards and pivot tables. These applications can assist businesses when making informed decisions, but they generally do not provide solutions. These solutions can be found by predicting the value of variables that they do not yet process but would benefit from knowing (Blum, Goldfarb, & Lederman, 2015). Prescriptive analytics, distinct from predictive, provides "direct insight into the consequences of different actions by uncovering the key cause-and-effect relationships" that influence the outcomes of an organization (Blum, Goldfarb, & Lederman, 2015).

Most organizations have not reached the level of predictive analytics. An inability to integrate and store the data has affected the granularity of data that is necessary for further analysis. The simplest way for companies to utilize the data is to describe and 'take stock' of what is currently happening and has happened. Within SCM, descriptive analytics generally provides insights to reports pertaining to production, financials, operations, sales, finance, inventory, and customers (Tiwari, Wee, & Daryanto, 2017). Real-time information and technology, such as analytical processing systems and visualization tools, are incorporated to identify opportunities and existing problems. These mechanisms can better illustrate the total stock in the inventory and the average amount of money spent per customer annually (Tiwari, Wee, & Daryanto, 2017). Tests that incorporate descriptive analytics can use quantitative and qualitative methods to deduce properties and make predictions about a population.

Predictive data analytics use statistics, simulation, and programming to explore data patterns in order to determine what will happen or is likely to happen (Tiwari, Wee, & Daryanto, 2017). These analytics use the organization's existing data – both structured and unstructured – to predict the value of variables. Specifically, this information can be utilized to forecast customer behavior, purchasing patterns, operations, and inventory levels. Park, Bellamy, & Basole (2016) incorporated predictive analytical capabilities and used testing methods with the SCM network database. They used a visual analytics-based decision support system and proposed that incorporating interactive visualization would enhance human cognition levels, thus increasing optimal decision-making.

It is imperative to specify the differences between the different levels within the hierarchical model of data analytics. Prescriptive analyses differentiate from descriptive or predictive analyses in that they provide direct insight into the consequences of different actions. They do so by uncovering the key cause-and-effect relationships that influence the outcomes an organization cares about. Compared to descriptive analytics that describe what occurred in the past, prescriptive analytics utilizes the decision-making mechanism and related tools (Rehman, Chang, Batool, & Wah, 2016). Research into SCM functions identified manufacturing and logistics/transportation as primary contributors to the prominent areas concerning prescriptive analytics. These areas adopted adequate prescriptive analytical techniques due to the various state-of-the-art systems, such as Cyber Physical System and ITS (Nguyen, Zhou, Spiegler, Ieromonachou, & Lin, 2018). Advancing to the level of prescriptive analytics would improve the organization’s operational, tactical, and strategic decision-making capabilities (Arunachalam, Kumar, & Kawalek, 2018).

Business processes relating to data analytics are subject to decision biases and could lead to sub-optimal performance between human and analytical systems. To avoid these biases, smart experiments can be implemented when designing and testing mechanisms that facilitate better decision-making (Eckerd, 2016). Smart experiments are best utilized at the level of prescriptive analytics due to their capacity to explain what will happen and why, thereby providing insight into recommended actions. Organizations conducting smart business experiments are able to delineate the operational and behavioral causes within big data that other methods cannot accomplish (Ancarani, Di Mauro, & D'Urso, 2016). Smart business experiments also provide an affordable and realistic method to implement new strategies, procedures, and policies (Croson & Gachter, 2010).

Given the efficacious results that smart experiments provide to an organization, it is surprising that they are not often utilized. Anderson and Simester (Anderson & Simester, 2011) propose that few firms have the technical skills to master such complicated tasks involved with dissecting past data. Seven rules are outlined for businesses that want to incorporate smart experiments. The first rule is to focus on individuals and think short term. To optimize results, experiments should measure the purchasing behavior of individual customers to disclose whether changes in their behavior lead to high profits (Anderson & Simester, 2011). The second rule involved in smart experiments is ultimately to keep it simple. When conducting experiments, it is ideal to use existing resources and staff rather than performing labor-intensive and costly tests. The third rule is to start with proof of concept, which can be achieved by changing one variable at a time to determine what caused the outcome. Rule number four suggests slicing the data as the results come in. Subgroups should be formulated from the data within both the control and treatment groups. Next, Anderson and Simester (Anderson & Simester, 2011) suggest out-of-the-box thinking. Experiments that involve entirely different sales approaches and engage in what-if thinking are more likely to yield innovative improvements. The sixth rule is to measure everything that matters. When actions in one channel affect sales in other channels, it is crucial to examine the results in terms of context. Lastly, the seventh rule outlined for successful and smart experiments is to look for natural experiments. Firms can learn to acknowledge when experiments naturally occur, thus educating themselves with little or no additional expenses (Anderson & Simester, 2011). Ultimately, using smart business experiments will better assist organizations to progress within the hierarchical model.

2.5. Data Architectures

While data analytics is defined by INFORMS as "the scientific process of transforming data into insights for the purpose of making better decisions"[1], data architecture is defined by how the enterprise data is stored, managed, and implemented within organizational systems and business intelligence (Lewis, Cormella-Dordo, Place, Plakosh, & and Seacord, 2001). Ultimately, data architectures aim to help organizations establish a common understanding of fundamental data elements (including analytics) used in various systems. A disciplined approach to data architecture outlines all elements relative to the data that is used when making informed business decisions.

[1] https://www.informs.org/About-INFORMS/News-Room/O.R.-and-Analytics-in-the-News/Best-definition-of-analytics

Individuals responsible for this data architecture must implement a design and structure-based framework. This involves separating the data into structured and unstructured data. Structured data, or data that adheres to a regular form, should have a syntax and a fixed-file storage allocation. On the other hand, unstructured data, or data that is irregular, may require an ad hoc file storage allocation. The Data Management Association (DAMA) outlines the nature of both structured and unstructured data. DAMA refers to data architecture as the overall structure of data and data-related resources as an integral part of the enterprise architecture (Cupola, Earley, & Henderson, 2014).

Data architecture within SCM is utilized in procurement analytics, which can be defined by issues relating to the decisions that are relevant to speed management, contract monitoring and compliance, procurement risk management, and value creation for stakeholders. Procurement analytics will assist managers and CPOs to evaluate suppliers based on the timeliness, quality, cost, and service levels of the delivery.

Procurement leaders need fundamental knowledge and skills to address digitization trends within SCM. CPOs are also involved in the development of robust data architecture and future analytics strategies. Despite these expectations, CPOs experience data integrity and quality issues. Deficits in these areas result in an inability to integrate and analyze the internal, external, historic, real-time, structured, and unstructured data, and are generally caused by practices relating to capturing and storing outdated data. Essentially, these roadblocks undermine their ability to support business partners and discover new insights that generate from effective data architectures. Santanam and Goul

(Santanam & Goul, 2018) investigated applications relevant to data architectures, analytics, and procurement strategies that define and assist with confronting these obstacles.

Given the undeniable increase of big data, it is imperative that organizations acknowledge and adapt to data architecture modernization. Instead of capturing data at the transaction level, data must be viewed historically and the focus must be on its life cycle. Consistent with findings from the CAPS Research report (Kull, Choi, & Srinivasan, 2016), the Center for Global Enterprise (2017) concluded that in order to be competitive within SCM, a consumer-centric approach is necessary. In other words, most organizations in SCM are shifting modernization strategies to emphasize improved customer relations. The most effective applications for consumer-centric modernization consist of real-time big data analytics, mobile, sensor and IoT technologies, and social media. These analytical platforms enable businesses within SCM to interpret their transactions with an increased level of data granularity. Incorporating rapid aggregation, visualization, and analysis of granular data can also help with moving forward on the model of data analytics. Utilizing practices that optimize data granularity not only increases their ability to analyze past or historical data (descriptive level), but also moves them toward a predictive and prescriptive level of analytics.

Another important concept in terms of data analytics references metadata or the descriptions and definitions regarding the information stored in a data repository. Within a data warehouse, there are four fundamental characteristics regarding the data. These characteristics consist of the meaning of the data, the validity of the data, the relationship between different data elements, and the granularity and source of the data. Specifically, organizations within SCM can track the who, when, and why of a purchase order by analyzing metadata. The metadata would consist of who created the order and document the history of when it was created and edited.

To identify the most notable impacts from upstream and downstream data, interviews were conducted with experts from 15 different organizations. These individuals were defined as procurement experts, which consisted of CPOs, analytics directors, and procurement managers (Shao & St. Louis, 2019). The majority of these procurement experts began their analytical journey by evaluating their spend analytics. This is deemed a logical starting point given that a successful automation of spend analytics normally accounts for having supplier master data and material category taxonomies. From the procurement experts, the process metric granularity involved in analytics from data architecture was a major obstacle. Recent digitization of procurement practices has increased the level of granularity to the tracking process metrics, contrary to the current procurement metrics that are outcome/output based.

Necessary resources, such as enterprise data warehouses, data marts, and data lakes, should be implemented when addressing problems with the data quality. If quality issues are not addressed at the outset, the entire analytics plan of action will be jeopardized. The action plan during the analytical journey identified the core capabilities as a strategic balancing of data assets and the governance of analytical capabilities.

Another deficiency in data architecture identified from the procurement experts was that most did not have a strong ability to integrate external data sources. Procurement experts can accommodate this deficiency by sharing their data with the suppliers. One of the companies interviewed had set up data sharing with their suppliers and they receive frequent performance information. They had also subscribed to another external source that evaluates supplier risk management. However, it is important to note that internal data cannot be shared with their suppliers (Santanam & Goul, 2018).

Multiple applications comprised of analytics tool suites and languages have been developed to support end users. Simple applications consist of business intelligence tools that predate more advanced data analytics algorithms, which include machine learning. These business intelligence tools can also be useful when generating reports and dashboards. Amongst the 15 procurement experts, a common feature in descriptive analytics was the use of dashboards that provided visual supplier information (Santanam & Goul, 2018). This visual information is simplified by reducing the data into sub-aggregations. Resources such as vendor analytics solutions and stand-alone applications allow data scientists to produce simplified results. Special reports, dashboards, and solutions can all be extracted from the results and provide more accessible information to procurement area leaders and managers.

Data architecture embodies the processes involved in storing, managing, and implementing data within organizational systems and business intelligence (Lewis, Cormella-Dordo, Place, Plakosh, & and Seacord, 2001), with the primary objective to enable a unified comprehension of fundamental data elements and analytics that are utilized across various systems. Within SCM, data architectures can optimize results when making informed business decisions through procurement analytics. Decisions relate to speed management, contract monitoring and compliance, procurement risk management, and the value creation for stakeholders. Data architectures embody the simplified processes when integrating external data sources. However, a research study that interviewed procurement experts identified a common obstacle: most experts did not have a strong ability or intention to integrate these external data sources (Santanam & Goul, 2018). Given the simplified adaptability and variety that this technology provides through data architectures, a further investigation into this identified lack of technology acceptance needs to be examined.

2.6. Technology Acceptance

Frequently organizations that invest in information technologies, such as hardware and software systems with advanced capabilities, experience lackluster returns from these investments. This productivity paradox is caused by a lack of utilization of these installed systems and is a primary concern in information systems research and practice (Sichel, 1997). The Technology Acceptance Model (TAM) encompasses empirical support and "consistently explains a substantial proportion of the variance (typically about 40%) in usage intentions and behavior" (Venkatesh & Davis, 2000, p. 186). The TAM theorizes the psychology behind the individual's behavior and intention to utilize a system, which is determined by two beliefs. One belief relates to the extent to which using the system will enhance their individual performance, called perceived usefulness. The other belief is whether the individual believes the system will be effortless, referred to as perceived ease of use (Venkatesh & Davis, 2000). The model theorizes the systems' external variables, such as system characteristics, development process, and training, as effective and relevant factors. These external variables are mediated by the two primary beliefs, with the primary objective of determining the individual's intention to use these systems. It is important to note that the perceived ease of use also affects and may predict one’s belief regarding the perceived usefulness. If they believe that the system is not easy to use, they will not believe in its usefulness (Venkatesh & Davis, 2000). Perceived usefulness has been a strong determinant relating to usage intentions across many empirical tests. However, perceived ease of use as a determining factor has been relatively overlooked (Venkatesh & Davis, 1996).

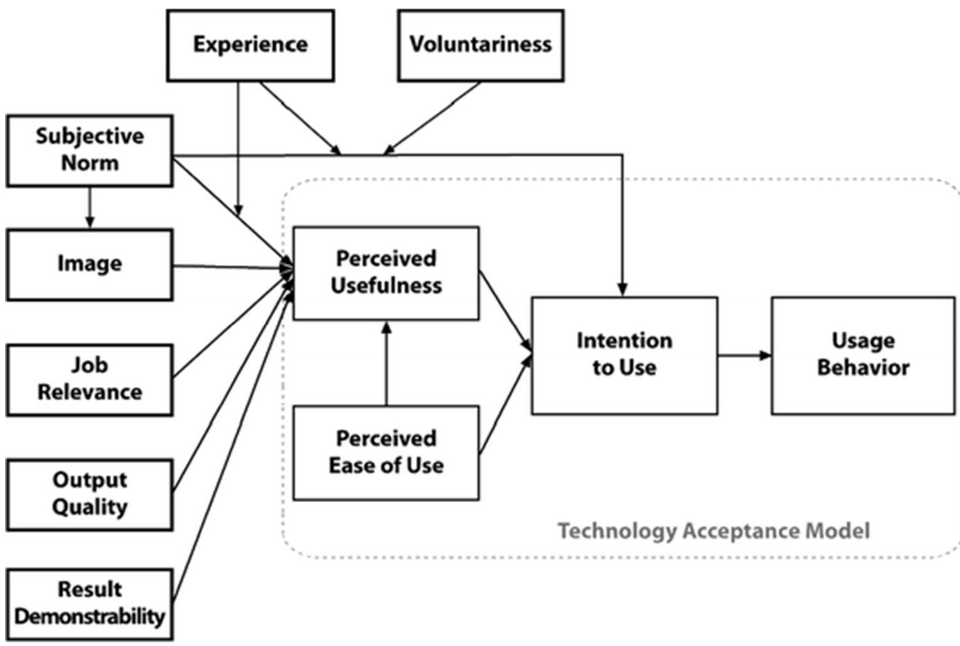

Figure 3: Technology Acceptance Model 2 (Venkatesh & Davis, 2000)

Vankatesh and Davis’s research aimed to use TAM to determine these key factors of perceived usefulness, usage intentions, and their relative constructs that account for the overall user acceptance. Determining these constructs will provide insight into how these determinants change over time when individuals acquire more practice with the target system. Thus, a new model of TAM, referred to as TAM2, was developed to incorporate additional theoretical constructs. The key determinants incorporated into TAM2 are social influence processes, such as subjective norm, voluntariness, and image. Subjective norm is defined as a person's perception that most people who are important to him think he should or should not perform the behavior in question (Fishbein & Ajzen, 1975). Past studies identified that subjective norm did not have a significant effect on an individual's intentions over perceived usefulness and ease of use (Davis, 1989). However, they did explain that additional research on subjective norm as a key determinant was necessary due to the potential influence on usage behavior that could be influenced by social influences. Voluntariness, also referred to as compliance, has a direct effect on the subjective norm. Hartwick and Barki (1994) identified this effect when they separated the respondents according to either mandatory or voluntary use, and concluded that subjective norm only had an effect in mandatory settings but not in voluntary settings. Voluntariness (or compliance) is defined as the extent to which potential adopters perceive the adoption decision to be non-mandatory (Agarwal & Prasad, 1997). Subjective norm has also been theorized by TAM2 to positively influence image. Moore and Benbasat (1991) define image as the degree to which use of an innovation is perceived to enhance one's status in one's social system.

TAM2 also included cognitive processes as key determinants contributing to user acceptance. These processes were identified as job relevance, output quality, result demonstrability, and perceived ease of use (Venkatesh & Davis, 2000). Job relevance is defined as the degree to which the target system is applicable to an individual's job, based on that individual's perception. Job relevance is distinct from the social influence processes in that it is a cognitive judgment that directly affects the perceived usefulness of the system. Relative to the overall capability to match their job's goal, individuals will also formulate perceived judgments on how well the system will perform these tasks, which is known as output quality. Individuals also fail to credit their increased job performance to their personal usage of the target system. This is known as demonstrability, which is defined as the "tangibility of the results of using the innovation" and it directly influences their perceived usefulness (Moore & Benbasat, 1991). Individuals will adopt positive perceptions regarding the target system if they continuously use it and produce positive results. However, if the system produces effective job relevance, but in an obscure manner, the individual will most likely misinterpret the usefulness of the system (Venkatesh & Davis, 2000).

Vankatesh and Davis conducted four longitudinal field studies to test TAM2, which encompass the key determinants of perceived usefulness and usage intentions, and how they contribute to overall user acceptance. TAM2 provided both social and cognitive influences that formed the underlying judgments of the perceived usefulness for the target systems. Conclusively, these constructs underlying one's perceived usefulness explained up to 60% of the variance regarding usage intentions (Venkatesh & Davis, 2000). TAM2 also demonstrated that subjective norm had a significantly greater effect on usage intentions than both perceived usefulness and perceived ease of use for mandatory systems. The subjective norm significantly influenced perceived usefulness due to social influences that affect their own usefulness perceptions and the utilization of the system to gain status in the workplace. They also found that an individual's increased use of the system can account for less reliance on social constructs when forming perceived usefulness and intention to use (Venkatesh & Davis, 2000). However, judgments regarding its usefulness for status benefits continued to evolve with gained experience. Subsequent findings outlined that perceived usefulness is greatly affected by cognitive determinants, such as job relevance and output quality. Individuals' perceptions on result demonstrability and the ease of use with the target systems were also significant (Venkatesh & Davis, 2000). Overall, it was concluded from the longitudinal study that the cognitive constructs remain significant over time, whereas the social influence processes do not.

2.7. Trust/Believability (Data Authority)

Poor data quality remains a consequential issue from a social and economic standpoint. Issues pertaining to analyzing, managing, and designing relevant data systems cannot be addressed until an individual or organization fully understands data quality in its entirety. Within the SCM domain, data quality must be understood in terms of the consumers' needs and desires. It is not a matter of the data simply being accurate; the data must be believable, relevant, and provide additional value.

The quality of the data must be defined from a consumer's perspective, not from a data production or Information Systems (IS) viewpoint. In this regard, researchers and practitioners can focus on quality data that is formulated by design. A framework developed by Garvin (1988) consists of eight dimensions that reflect the quality of the data: performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality.

Research by Wang and Guarascio used factor analysis to identify all underlying structures and dimensions related to data quality. Twenty dimensions were identified from the survey respondents and explained 73.9% of the total variance. These dimensions are: Believability, Value Added, Relevancy, Accuracy, Interpretability, Ease of Understanding, Accessibility, Objectivity, Timeliness, Completeness, Traceability, Reputation, Representational Consistency, Cost Effectiveness, Ease of Operation, Variety of Data & Data Sources, Conciseness, Access Security, and Appropriate Amount of Data Flexibility (Wang & Guarascio, 1991). From these dimensions, consumers of data most notably take into account the traceability, reputation, and the variety of data and data sources when analyzing its accuracy. Ultimately, they must be assured that the data contains no errors, they must have the ability to trace, verify, and audit the data, and they must be confident in the data's reputation and its source. Believability was the most important dimension of perceived data quality. The trust and believability of the quality of the data has a direct effect on the individual's overall perceived usefulness and usage intentions. Data consumers must trust in the accuracy of the data and possess fundamental knowledge in order to utilize the data and incorporate relative systems, thereby increasing user acceptance.

2.8. Conclusion from Literature

As research has shown throughout the literature review, data analytics have not been utilized to their full potential within SCM. In the context of the literature review, this problem was investigated by first examining the organizational structure for data management. In doing so relevant findings were identified within the first three levels of data analytics based on the social technical systems theory, saliency, and change management. Research findings in these areas helped to identify why organizations have not moved beyond descriptive analytics, and propose solutions on how to progress up the hierarchy.

First, the STS theory was discussed due to its known value and underutilization. The STS theory is relevant for organizations to adapt because it operationalizes business practices. This theory uses interacting sub-systems that involve talented individuals working together, following processes, utilizing technological systems, operating within an infrastructure, and sharing cultural norms. By examining each sub-system, a better way to identify and modify relevant issues was developed. For example, organizations cannot place full responsibility on one individual; they must examine team cohesion (Siebold, 1991). To adapt this theory within business practices, researchers found that organizations can reduce the external complexities by increasing the internal complexities (Sitter, Hertog, & Dankbaar, 1997). The STS theory emphasizes that the 'social' and 'technical' components of an organization are interdependent and change simultaneously. To move up the model by utilizing this theory, organizations must emphasize customer behavior, understand the process involved in generating data, and apply evidence through critical thinking (Baum, Laroque, Oeser, Skoogh, & Subramaniyan, 2018). Furthermore, the foundation that organizations can adapt to outline why they are trapped within the model was discussed, and the sub-system of technology was elaborated on by investigating big data.

The most significant challenge within the era of big data has been how to manage it and how to determine what is important (i.e. saliency). Saliency within big data helps to explain how users can explore and comprehend large amounts of information (Matzen, Haass, Divis, Wang, & Wilson, 2018). Saliency provides key insights into why organizations stagnate on the level of descriptive analytics. The lack of strategic planning is caused by management that may not be fully educated and experienced with big data. Ultimately, management must change for organizations to fully utilize data analytics, thus, moving up within the model. For management to change, they have to first acknowledge that there is a problem, and then through strategic planning, they can devise a solution. However, for management to change, they must be convinced that their additional effort provides a return and that the return will outweigh the risk.

In order for an organization to move up the hierarchical model, they must understand and possess the characteristics accounting for each level until they have reached the top. Most firms are settled at descriptive analytics through dashboards, and few are moving up to higher levels of advanced data analytics. If managers could overcome the issues by implementing, predicting, and evaluating the higher levels of data analytics, this could result in an adequate solution.

Higher levels of data analytics are complex and not fully salient; thus, they require an in-depth investigation of why managers may not be comfortable implementing these higher levels and how they can be achieved. Applications such as dashboards and pivot tables help organizations make informed decisions but they do not present predictive and prescriptive solutions. Moving up to predictive and then prescriptive analytics would predict the value of unaccounted for variables and uncover key cause-and-effect relationships that would greatly benefit them. Smart business experiments are a proven solution that results in the optimization of data analytics. However, decision biases could be the leading cause of their current sub-optimal performance. Unfortunately, few firms encompass the technical skill required to master such complicated tasks when dissecting past data (Anderson & Simester, 2011).

To assist in such complicated tasks, organizations can establish data architectures through a design and structure-based framework that outlines all elements relative to the data. The observed inability to integrate and analyze data architectures has been linked to CPOs capturing and storing outdated data (Santanam & Goul, 2018). Roadblocks when outlining data architectures result in issues that pertain to discovering new insights, validating the data, and determining different relationships between data elements. From interviewing different organizations, the primary deficiency was found in the process of data granularity and the use of external data sources. However, resources such as enterprise data warehouses, data marts and lakes, and advanced algorithms that include machine learning can be implemented to account for these issues.

Given the simplicity of procuring data architectures that result in managing complex data, organizations still demonstrate a strong inability and lack of intention to integrate external data sources and technologies. Moreover, organizations that possess such systems experience lackluster returns from these investments due to a lack of utilization. Findings from the Technology Acceptance Model (TAM) were investigated due to its empirical support when evaluating usage and intentions (Venkatesh & Davis, 2000). TAM demonstrated that lack of performance was related to the lack of user's perceived usefulness and perceived ease of use. However, these determinants change over time because of acquired practice when using these target systems and technologies. Thus, TAM2 expands into the determinants of perceived usefulness such as social influences, subjective norms, result demonstrability, and cognitive influences, which were deemed significant factors underlying judgments based on the user's perceived usefulness and overall technology acceptance (Venkatesh & Davis, 2000).

The observed roadblocks identified within technology acceptance have provided insight into why organizations have not been able to advance into higher levels of data analytics. However, these issues cannot be fully understood until the data quality has been addressed in its entirety. Data quality within SCM must first be accounted for in terms of its believability, relevancy, and the additional value it provides. Research into the underlying structures and dimensions related to the quality of data outlined 20 factors (Wang & Guarascio, 1991). Most notably, they found that consumers of data primarily take into account the traceability, reputation, and the variety of data and data sources when analyzing its accuracy. Ultimately, the trust and believability of data directly affects the user's perceived usefulness and usage intentions, as discussed within technology acceptance. In conclusion it has been found that these findings, as a whole, provide a meta-analysis to support the hypothesis as to why organizations have been unable to effectively implement predictive, prescriptive, and cognitive analytics. These issues can be investigated in greater detail by establishing findings within a large organization. This is done in the following sections of the dissertation.

3. METHODOLOGY

To fully investigate the true cause of the underutilization of data analytics systems requires an in-depth investigation into the issues. A case study using a firm in a supply chain heavy industry with in-depth interviews of multiple key people within the organization can offer this insight. A case study sometimes presents challenges for generating scientific conclusions from qualitative analysis, but the proper controls in the development of the study can overcome these challenges (Markus, 1983) (Lee, 1989) (Yin, 2017).

3.1. Research Questions

The issues identified within SCM motivated two fundamental questions:

1) Why don't organizations create a strategic advantage by utilizing predictive and prescriptive analytics?
2) How can the results of predictive and prescriptive analytics be made more salient?

New insights about these questions should enable organizations to progress up the analytics hierarchy.

3.2. Case Study Scientific Research

For research questions such as theses, it is exceptionally difficult to utilize generally accepted data analysis. A case study methodology is needed to understand all the nuances of the business processes and dissect this detailed problem. To conduct a scientific research study while utilizing the case study research methodology, researchers have developed a framework that must be adopted (Yin, 2017). The framework facilitates controlled observation and deductions to allow for replicability and generalizability, which are all needed to qualify a case study as scientific research.

3.2.1. Making Controlled Observations

Critics of case study research point out that it most often fails to utilize either laboratory controls or statistical controls when making observations. Therefore, to test theories that utilize the case study method, one must make controlled observations using natural controls within the case environment. Controlled observations in a case study require natural controls. Case study researchers must derive predictions that take advantage of natural controls and treatments either already in place or likely to occur (Lee, 1989).

A simple but clear example of this occurs in a test of the people-determined theory in which a particular accountant, upon moving from his position in corporate accounting to controller in one of the divisions, changes from being an advocate of the financial information system to one of its opponents (Markus, 1983). This particular test controls for or holds constant the people factors by focusing on just one person (the accountant), and it varies or treats the situation external to the person by observing his move from corporate accounting to a division (Lee, 1989).

In this example, through the way in which the case study was conducted, the researcher had a natural control of the person, which remained constant, while the environment in which the person was placed was changed. Focusing on just one person and altering the environment (the treatment) takes advantage of the person's move from one part of the organization to another. Therefore, controlled observations can now be made about interactions with the environment and they can be compared between the different scenarios.

3.2.2. Making Controlled Deductions

In statistical analysis, the rules of algebra are used to determine the validity of deductions that involve mathematical propositions. In qualitative analysis, no established set of rules, such as algebra, can be applied to verify the validity of deductions involving verbal propositions. To apply controlled deductions, one must remain cognizant of the fact that mathematics is a subset of formal logic, not vice versa.

By applying the Transitive Property of Equality in basic algebra, one allows for controlled deductions when direct observations are not possible. The Transitive Property states that if $a = b$ and $b = c$, then $a = c$. Therefore, when making logical deductions, one can use verbal propositions, for example, the prediction that Socrates is mortal can be deduced from two other verbal propositions: All men are mortal (the theory) and Socrates is a man (the facts or initial conditions) (Lee, 1989).

MIS case researchers find themselves in good company with regard to analyses that utilize the medium of verbal propositions, as opposed to mathematical propositions. Consider biology and the theory of evolution. For Darwin, words and sentences were the medium of logical deduction, not numbers and mathematics (Kaplan, 1964).

3.2.3. Allowing for Replicability

Replicability is also a key component in scientific research. Using the same methods and theories, an independent investigator could apply the methods tested in the original case study to a different set of initial conditions, thereby resulting in different predictions. In business research, this can be accomplished by examining the same phenomenon either across companies or between different discrete departments that provide different functions within an organization.

3.2.4. Allowing for Generalizability

Generalizability is another important characteristic of scientific research. In case study research, non-replicable events are vulnerable to the charge that their findings cannot be extended to other settings. For a theory to be generalizable to other sets of empirical circumstances, the case needs to be confirmed by additional experiments that test it against other sets of empirical circumstances.

Generalizability is a quality that describes a theory that has been tested and confirmed in a variety of situations, whether such testing is conducted through case research, laboratory experiments, statistical experiments, or natural experiments. As such, generalizability poses no more, and no less, of a problem for MIS case research than it does for the studies conducted in the natural sciences. In taking this position, the MIS case researcher would, again, be in step with the natural science model (Lee, 1989).

3.3. Case Study Organization

To conduct extensive interviews with stakeholders, SunWest Fruit Company has offered to make their managers available. SunWest Fruit Company is a privately owned, vertically integrated farming operation that controls all aspects of production from field to supermarket delivery. The company farms over 9,000 acres, and it harvests, packs, and ships every piece of fruit in-house. It is consistently listed as one of the top producers in its field (American/Western Fruit Grower, 2012). This level of in-house production requires that the organization constantly evaluate its product mix of over fifty varieties of peaches, plums, nectarines, and oranges. It also has more than twenty packaging types and consumer brands per variety. Strategic decision-making encompasses a two- to five-year horizon, because trees need four or more years to reach maturity and begin producing high quality fruit. Managers also need to plan for packing different sized bags and boxes, which each require specialized equipment that needs to be procured, as well as the space required to clean, pack, and store the finished products.

SunWest Fruit company derives its value for shareholders through operating a precise supply chain that delivers fresh fruit from the fields to the retailers through a sorting, packaging plant and wholesale sales process. This chain of processes requires many decisions that can directly affect the organization's bottom line and which are complex to model. This value chain that is a component of the overall supply chain requires decisions about field management, which include planting, watering, fertilizing, pruning, and picking. When the product arrives at the packing and sorting facility, decisions are made involving quality grading, packaging size, and storage availability for inventory. With regard to the sales process, external market forces dictate the price and sales volume. These forces that influence the product's salability will feed back into the packing and field operations to ensure the product that is demanded is what the organization produces for the following year.

The many moving parts of the models in this industry decrease the saliency of the variables of any one part of the value chain, thus reducing the ability of the decision makers to clearly understand how to implement predictive and prescriptive analytics. This provides a complex environment that can be uniquely leveraged to understand the difficulties of advanced analytics, and an opportunity to speak in depth with the individuals who are responsible for the analysis and decision making.

3.4. Interview Subjects

Within SunWest Fruit Company, four individuals are responsible for the strategic decision-making of the organization. The general manger oversees the entire organization and must approve the decisions of the department heads to ensure that their individual strategies align with one another and the overall strategy of the organization. The first functional area that SunWest Fruit uses to generate value is growing the fruit in the fields. It is the field manager's responsibility to grow the fruit in a way that maximizes the value of the orchards and maintains a constant supply of ripe fruit to the packing plant, thereby preventing spoilage in the field. After the field, the next step in the value chain is the packing facility where the fruit is sorted, packed, and temporarily stored in preparation for shipping. It is the packing general manager's role to balance the costs of operating the facility with the goal of packing the fruit needed for the orders managed by the sales department. The sales department's responsibility is to be aware of the economic factors in the marketplace and to negotiate prices with the buyers from the grocery distributors. The sales manager must balance the value of long-term future contracts vs. exploiting swings in market price that result from weather and economic factors. There is also an IT manager whose job is to create and maintain the enabling infrastructure for the other managers. Therefor I interviewed the sales manager, field manager, IT manager, controller, and the general manager to investigate these issues with the following field survey instrument.

3.5. Field Survey Instrument

The field survey will consist of interviewing five senior managers at SunWest Fruit: the general manager, plant manager, farming manager, sales manager and IT manager. The interviews will consist of three sessions to gain insight into the subject matter, which will allow the questions in the subsequent sessions to address the unique challenges of the organization that are identified in the prior sessions. The first phase will consist of asking questions about the key performance indicators of the organization. After a break of several days to adjust the questions, the next session will be a conversation about how the organization already uses or could use predictive or prescriptive analytics to improve on those key performance indicators. After another break of several days, the third session will attempt to explore what would be required for the organization to use prescriptive and cognitive analysis more widely and effectively.

The survey was structured this way to reflect the change management literature. That literature states that change will only take place if managers recognize there is a problem, believe the problem can be solved, and believe the reward from solving the problem is worth the effort required to solve the problem. Without key performance indicators, managers cannot know if a problem exists. Hence phase 1 is required to see if the organization can even identify its problems. Phase 2 is required to see what problems exists. Phase 3 is required to see if the problems can be solved and whether it is worth the effort to try and solve them. A three phased approach is the only way to do this.

3.5.1. Phase 1: Key Performance Indicators

What are your KPI (Key Performance Indicators) for your operations?

- How do you track your performance for those KPIs?
- Reports –
    - What kind of reports do you generate?
- Drill Down –
    - What types of tools are available to drill down to find the root cause to issues that could be flagged by the reports?
- Dashboards
    - Are dashboards available? What kind of data do they show?
    - Are they real-time?
- Forecasts
    - What types of forecasts are made? Are the forecasts checked ex post to determine their accuracy?
    - What data do you use to make forecasts?
    - Do you rely on expert opinion to make forecasts?

    - Whose expert opinions do you rely on to make forecasts?
    - When making forecasts, do you rely more on data or expert opinion?
- How have you changed your operations (taken actions) as a result of forecasts made or data that you collected?
- What aspects of your operations do you think analytics could help you improve?

3.5.2. Phase 2: Predictive and Descriptive Analytics

(Based on session 1 we will compile a list of how data, better forecasts, or experiments might help them)

- Would you like to forecast:
    - Demand
    - Yield
    - Weather
    - Water
    - Pruning
    - Produce Quality Metrics
    - Product Mix
    - Economic Environment
    - Regional Yield Averages
    - Yield per Block
    - Costs per Block
    - Cost of Packing
    - Labor Costs

        - Warehouse Space
- How happy are you with your forecasting ability? If not satisfied, why aren't you satisfied?
- What would you like to forecast that you currently are not forecasting? Why aren't you currently able to forecast those items?
- What data would you like to have that you currently do not have?
- What do you think could be done to make the expert opinion that you rely on more accurate?

3.5.3. Phase 3: Prescriptive and Cognitive Analytics

(Based on sessions 1 and 2, a list of things we think they could do, and how they could do it will be compiled.)

- If this could be done, would it be helpful to you?
- If it would be helpful, and if it could be done this way, would you do it?
- If they say they would not do it, is it because
    - Problems are not that severe
    - They do not feel that it is possible due to:
        - Lack of skilled employees?
        - Will managers just not accept it?
        - It is impossible to get the needed data?
        - The process is too complicated?
        - The company does not believe in evidence-based decision making?
    - The benefits are not worth the cost.

- Is the cost too great?
- The benefits are too uncertain?

4. RESULTS

The results of the field study provide real-world insight into the challenges that an organization faces when attempting to increase the sophistication of their data analytics and move up the data analytics hierarchy. This study is necessary to evaluate the hypotheses introduced by our previous study (Glassman, Shao, & St. Louis, 2019). The different managers in the organization should each have unique views of the same data problems as they each focus on different segments of the value chain but are highly dependent on each other. This tactical view of the strategic decision-making information systems should provide significant insight into how the organization can build the prescriptive and cognitive analysis into their business processes.

4.1. Phase 1 Results: Key Performance Indicators

The findings presented in this section are organized by participant. The discussion of the findings from each participant is organized by major finding. Within the discussion of each major finding, direct quotations from the interviews are presented as evidence. In the following sections I present the finding from the interviews with the sales manager, field manager, IT manager, controller, and the general manager.

4.1.1. Sales Manager

Table 2: Phase 1 Sales Manager Summary of Responses

Sales Manager	
KPI	Profitability (ROI per block/acre)
Reports	Pack out report determines (grow>pick>pack yield) Equivalency units used to normalize box size
Drill Down	No drilldown since reports are manually created and combined with other reports from ERP and PMS. Also it's in the past and it's moving so fast, so don't have time.
Dashboards	He said no but from site visit there are dashboard he uses on a daily basis. But they track fruits as its moving through the production phases, not the KPI.
Forecasts	Forecasts are done via reports from the field on the status of the fruit to determine what is available when, and the sales team is reactionary to this information with little long term planning (only week to week).
Opinion of Data	Mostly rely on expert opinion on what fruit is ready and estimated quality/quantity. Data is normally too old to be actionable.
Room for Improvement	Having the product being tracked by field on a longer term horizon. Would be useful to forecast more than a week out. Most of the reports don't reflect the real causes of variances. Due to the recent pandemic, demand skyrocketed 50%. It would have been nice to have a longer time horizon on production to have been able to fulfill quicker.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The sales manager stated that accurate forecasts were needed because, "You have to manage the crop to obtain the customers' supplies for a certain period of time." When forecasts were accurate, the sales manager added, harvesting operations could be adjusted to minimize waste and meet customer demand: "Having an accurate forecast enables you to decide whether or not you want to harvest x amount of fruit per week or whether you want to harvest significantly more or less than that number." The sales manager expressed the perception that improvements to existing forecasting capabilities would be "Extremely beneficial."

The sales manager perceived the usefulness of forecasting as limited in part by the quality of the data on which forecasts were based. He said: "One of the problems pertaining to developing forecasts is that you are only as good as the information and the data that you program into the system." In describing why the data were often of low quality, the sales manager suggested that the complexity of production was difficult to model, and that data were therefore unlikely to adequately capture the relevant predictors: "There are a lot of variables where the numbers won't indicate what is actually taking place." The sales manager suggested that the potentially intractable problem of developing an adequate model was associated with industry-specific challenges: "There are a lot of moving pieces within the data of a production facility, and the numbers might say one thing, but in actuality it might be something else. This is where I believe the produce industry becomes very hard."

Major Finding 2: Management rarely checks the accuracy of expert forecasts for yield.

The sales manager said of how he and his team produced forecasts, "Sometimes it's expert opinion and other times it is a combination of both [expert opinion and data]. Historically, a lot has been driven by expert opinion." When asked if the team's forecasts were checked for accuracy, the sales manager stated: "We do have an estimate regarding the crop for the upcoming season and at the end we will compare what our estimate was versus what we actually got." However, the sales manager expressed that most forecasts based on expert opinion were not checked: “For most situations, we probably won’t [analyze whether the forecasts were accurate].”

Major Finding 3: Pricing for a majority of the yield is contracted.

When asked about market pricing, the sales manager stated: “The dynamic [market] pricing is driven by very simple economics, such as supply and demand.” The sales manager discussed contracted pricing in Phase 2. His Phase 2 responses in support of this major finding are provided in the discussion of Phase 2 findings.

Major Finding 4: The information being collected does not help with decision-making.

The sales manager stated, “There is a lot of value in data,” but he added, “you are only as good as the information and the data that you program into the system.” He indicated that the value he perceived in data was potential, however, and that current data were not yet helpful in decision-making: “More data is being integrated [into forecasting processes], but it is still pretty rudimentary at this point.”

4.1.2. Field Manager

Table 3: Phase 1 Field Manager Summary of Responses

Field Manager	
KPI	Quality control in delivering production from field to packing facility (yield)
Reports	Pack out report determines (grow>pick>pack yield) Equivalency units used to normalize box size Lots of paper tags are used to correlate this report via the ERP and PMS
Drill Down	No drilldown since reports are manually created and combined with other reports from ERP and PMS Any drill down is done in quality control meetings and more qualitative in nature.
Dashboards	No dashboard on ex post reports.
Forecasts	Analyze the estimates for citrus, both from crop sizing standpoints and the overall yields (currently only week to week).
Opinion of Data	All expert opinion is written in hand written notes which are rarely codified.
Room for Improvement	Give a field estimator the ability to compare our inputs versus what we are doing in terms of production. A way to dashboard this would be useful. Track what labor actions are cost effective.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The field manager said of existing forecasting capabilities: "We analyze the estimates for citrus, both from crop sizing standpoints and the overall yields. Then, we continue to gather and compare that information as we go through the year. We also have a clean pick schedule that's in Excel format and we will compare our estimates versus the actual numbers." The data was "experience-based. We go out and assess each block. We also use a caliper to provide size estimates, which assists in determining the subsequent size growth in an ideal climate or situation." Forecasting was used for quality control. The field manager stated: "You may have to harvest earlier than you anticipated to keep the fruit from becoming oversized. We may manipulate cultural practices through irrigation deficit or fertility management to help us reduce the size structure if it's a light crop."

The field manager stated that the usefulness of existing forecasts was severely limited by an inability to perform analytics on aggregated, year-over-year crop-yield data in order to "create dashboards that produce analytical trends. If we could create tables or dashboards that produce aggregated annual yield data to base our determinations off of, that would be an ideal scenario." The ability to aggregate yearly cost data would be of particular value, the field manager added: "If we were able to analyze that [annual labor cost] data year over year, block after block, and then compare that to the yield output through aggregating the data for evaluation purposes, that would be a great philosophy." However, yearly data aggregation was impossible in the existing forecasting system, which was based on, "our staff having to go back to run a report and examine the information year after year on a piece of paper."

Major Finding 2: Management rarely checks the accuracy of expert forecasts for yield.

The field manager provided inconsistent data in relation to this major finding, stating that a process was utilized to check forecasts based on expert opinions for accuracy. Expert opinions were based on data collected by visiting fields. The field manager stated: "It's more experience-based, we go out and assess each block. We also use a caliper to provide size estimates." Of the process used to check expert opinions, the field manager stated: "We have a clean pick schedule that's in Excel format, and we will compare our estimates versus the actual numbers." The field manager did not state that the results of accuracy checks were documented or aggregated, however, or that forecasting processes were adjusted on the basis of historical accuracy.

Major Finding 3: The information being collected does not help with decision-making.

The field manager affirmed that data on weather, yield, demand, quality, and labor costs needed to be aggregated year-over-year to make decisions that would maximize efficiency, but he added, “The one thing that we currently do not have is the ability to aggregate yearly data and create dashboards that produce analytical trends.” The field manager also stated in the same response, “If we could create tables or dashboards that produce aggregated annual yield data to base our determinations off of, that would be an ideal scenario.” In providing an example of why aggregated, yearly data on factors such as weather and yield were needed for decision-making, the field manager said, “If we can look at historicals, and similar-degree days or temperature correspondence, and see how that relates to, let's say, 2012, if that was a similar year, we could see how that affected our commodities.”

4.1.3. IT Manager

Table 4: Phase 1 IT Manager Summary of Responses

IT Manager	
KPI	Net revenue – keeping IT expense down
Reports	Reports via the ERP and PMS. Data warehousing isn't done efficiently. Year over year tracking is difficult because so many external variables are not tracked.
Drill Down	Some reports are actually dynamic and are clickable for drill down. But many reports are not, and the information on variance needs to be moved to other search fields to do drill downs. Often new reports serve as the drill down.
Dashboards	Have a very new system that allows dashboards, but most people don't know how to use or ask the question the right way.
Forecasts	Forecasts are made and there is high variance in the results of the forecasts, but the quality and accuracy of the forecasts isn't tracked efficiently. Forecasts for a particular block on a particular day.
Opinion or Data	Date at the block level is stored in the ERP. No expert opinion is used.
Room for Improvement	The business intelligence/analysis side of things needs to be expanded. It's complicated considering that it's already there and accessible, but the people who would know what to do with it don't necessarily know what data is available. Data is there and we can access it, however, knowing what is important can be challenging.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The IT manager stated that existing forecasts were used to predict crop yields in order to maximize harvesting efficiency while minimizing labor costs. The forecasts, the IT manager explained, include "harvest forecasts, which are forecasts on how much of a commodity we intend to receive from a particular block or on a particular day." The data on which the forecasts were based include "the history of a particular field, along with factoring in conditions such as weather and other seasonal adjustments." For harvest forecasts, the IT manager added, "In terms of the accuracy of that forecast, there is probably a good 5-15% variance." The IT manager emphasized that data were not aggregated across fields to make forecasts for specific fields, but that predictions were instead based on previous harvests in the specific field for which the forecast was made: "We're not comparing field A to field B to conclude what field B is going to do this year. We're looking at prior years of that same field, which incorporates all the same variables that existed in prior years."

The IT manager explained that harvesting forecasts need to be highly accurate: "We need to make that determination as accurately as possible because we want to ensure that we are not overpaying for labor and we're doing it as efficiently as possible." Accurate forecasts are also needed to ensure that labor demands in later stages of the harvesting and distribution process are met but not exceeded: "It is very important to keep the amount of fruit coming into the facility and the amount exiting the facility in somewhat a balance. We want to avoid the product spoiling or not having enough product to ship out." The IT manager described more accurate forecasts as impossible to obtain: "We know there is going to be variance no matter what we do, so we have to make sure the variance is acceptable." Accuracy was limited by the difficulty of identifying the most significant data. Any improvement in the process of identifying the most relevant data would improve forecasts, the IT manager said: "A comprehensive format that pinpoints the useful data points for specific individuals would be of value. The data is there and we can access it, however, knowing what is important and ignoring the rest can be challenging."

Major Finding 2: The information being collected does not help with decision-making.

The IT manager expressed that data-based forecasting capabilities were limited by staff inexperience: “We just started getting into some of the business intelligence/analysis side of things.” Unlike other participants, the IT manager said of the data needed to make useful decisions, “It’s already there and accessible.” However, the data were not useful in decision-making because the IT manager and his team had not identified a means of “getting that information translated in a comprehensive format that pinpoints the useful data points for specific individuals.” As a result, the IT manager said, “The data is there and we can access it, however, knowing what is important and ignoring the rest can be challenging.”

4.1.4. Controller

Table 5: Phase 1 Controller Summary of Responses

Controller	
KPI	Profitability (ROI per block/acre). The field is concerned with yield, the packing house metric is productivity, and the sales metric is based on price.
Reports	Tracked via cost in ERP system, cost accounting at box per acre and associated expenses. About two thirds of our sales is on contract pricing, and the rest is on market pricing. Packout report is used to generate the data. These reports show how many boxes were packed and how many bins were used to get those boxes. It's done by grower and by block, so we know exactly which block is producing how much.
Drill Down	Many reports have drill down capabilities and are clickable.
Dashboards	Dashboards are available, but I don't use them because they don't provide useful information for the kind of reporting that I conduct.
Forecasts	Last year's data is used to generate forecasts of the upcoming season.
Opinion or Data	Season Forecasts are made using data, but week to week forecasts are expert opinion they do not have anything that will make data-based projections because it changes drastically based on a multitude of variables.
Room for Improvement	Having the expert point being tracked by field on a longer-term horizon (more than a week out) would be useful to forecast. Field cost; the analytics could help show what we've done in the past and if it's valid or not to help shape field management strategy and optimize the process.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The controller stated that at the beginning of the season, "There is a report that projects how [many bins of citrus and mandarins] we are expecting for the season, and it's updated on a weekly basis until the season is over." The forecasts were based on expert opinions, the controller explained: "It's determined by the field managers and the foremen that go in and examine the tree, the buds, and the size. From there, they will do an estimate on each block for what they believe that field will generate." Like the sales manager, the controller expressed the perception that useful forecasting was impossible because of the difficulty of appropriately modeling the variables: "[Field managers and foremen] do not have anything that will make projections because it changes drastically based on a multitude of variables."

The controller added that if more accurate forecasts were possible, they would be valuable: "Ultimately, analytics could tell us if some of the field work we're doing is really benefitting us within the big picture. In the packing house, analytics could tell us if we are being efficient in our flavor versus quantity." More accurate forecasting of labor demands would contribute to reducing waste and costs, the controller added: "If you could put together a better estimate or fine tune what's going to be coming into the plant, you could determine the head count more efficiently than we are doing now." With existing forecasting capabilities, the controller said, "Sometimes we have employees come in and there's no work to do because the food didn't come in."

Major Finding 2: Management rarely checks the accuracy of expert forecasts for yield.

The controller stated that yield forecasts were determined by the expert opinions of individual field personnel: "It's determined by the field managers and the foremen that go in and examine the tree, the buds, and the size. From there, they will estimate on each block for what they believe that field will generate." The controller added that the crop yield forecasts were not systematically documented for later checking, but were instead used to make on-the-spot decisions, as discussed in relation to Major Finding 1: "[Field managers] react almost on a day-to-day basis of going out there and taking a look and saying, ‘Okay, this one's ready. Let's pick this today.’”

Major Finding 3: Pricing for a majority of the yield is contracted.

The controller stated that a majority of the produce was sold at contracted prices, and contrasted the reliability of contracted prices with the unpredictability of market prices: “About two-thirds of our sales is on contract pricing, and the rest is on market pricing. Contract pricing is determined for the season, and the market pricing is determined by whatever the day may bring.” The controller explained how contracted pricing worked in practice, stating, “The standard box [of produce] has a set price that is determined for the season. For our major vendors, we went out and generated contracts based on a certain quantity for the year.” The controller added of pricing contracts, “It doesn’t state the specific size, but it is based on quantity and a base price for that quantity. If the packaging changes from the base, there will be an upcharge.”

Major Finding 4: The information being collected does not help with decision-making.

The controller stated that the data being collected were not relevant and that the forecasts based on them were not useful in decision-making. As an example, the controller stated that the information collected about harvested quantities was not useful in predicting marketable crop yield: “When they pick it in the field, they're [collecting data] on bins. Now, when they're picking it in the bins, they're not being overly selective.” Bins vary in size, and a substantial percentage of harvested fruit is discarded during quality control before the usable fruit is packaged in cartons. As a result, the controller said, “you can anticipate bins, but that's not necessarily how it would relate to actual cartons.”

4.1.5. General Manager

Table 6: Phase 1 General Manager Summary of Responses

General Manager	
KPI	Profitability (ROI per block/acre), cost accounting
Reports	Basic excel spreadsheets; most reports generated by ERP aren't formatted to answer the right questions. Pack out report is used to generate the data.
Drill Down	Excel pivot tables.
Dashboards	No useful overall dashboard since reports have to be manually combined.
Forecasts	Huge inefficiencies because accuracy isn't tracked
Opinion or Data	Combination of data and expert opinion which make the data for forecasts very sloppy and not reliable.
Room for Improvement	Taking the information from our forecasts and evaluating it against our results, thus refining the accuracy of that information would be a plus from analytics. A lot of that is driven by the value to the field operations, and they would find value in their costing models for harvest and return-to-farm in case they are off on their estimates.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The general manager said of existing forecasts, "There is a rolling, three-week harvest estimate that is produced by commodity and size." The forecasts are only useful as rough guidelines, the general manager stated: "The sales team uses them to plan for sales, we use it to plan our material needs against what the sales will have. Ultimately, the forecasts are a rough guideline and then it's reactive after that." As an example of what he meant by "reactive," The general manager described preparations made based on inaccurate forecasts as needing to be adjusted: "For example, if the sales team is expecting medium-sized fruit and we receive small-sized fruit, they must react by adjusting their sales strategy with the individual customers that they have."

More accurate forecasts would be valuable, the general manager said, because existing forecasts are “not anything that I feel is accurate enough to build costing models against because of the changes from the quality of the product coming in and the reality of sales produced.” The general manager added, “Ultimately, there’s a large inefficiency by not having accuracy dialed in,” but attempts to increase accuracy have been unsuccessful: “Getting all of that [accuracy] dialed in would have great value and something that I’ve tried to do by myself over the years, but it continues to be on an as-needed basis.” The general manager added that a specific, useful improvement to forecasting would be, “Taking the information from our forecasts and evaluating it against our results, thus refining the accuracy of that information, would be a plus from analytics.”

Major Finding 2: Management rarely checks the accuracy of expert forecasts for yield.

The general manager described the “rolling, three-week harvest estimate” as developed from expert opinion by “observing what we have to work with and creating a plan. That plan is developed from the personnel here with many years of experience, all the way through from sales to production.” The general manager added that the forecasts were not checked for accuracy: “The accuracy of those forecasts is not validated, we use it as a guide for planning.” Instead of checking forecasts for accuracy, the general manager said, “Changes are made on the fly.” The general manager stated that a checking procedure would have value: “I believe taking the information from our forecasts and evaluating it against our results, thus refining the accuracy of that information, would be a plus from analytics.”

Major Finding 3: The information being collected does not help with decision-making.

The general manager indicated that the information being collected was not useful in decision-making because its accuracy was doubtful. The general manager said that forecasts related to the market were “mostly from history and anecdotal current information. It seems to give me some guidance, but I don't have a real formal process for feeling like I've got accurate dashboard information to make decisions from.” The general manager added, “there’s a large inefficiency by not having accuracy dialed in.”

4.1.6. Phase 1: Cross-Participant Comparisons and Summary

In their Phase 1 responses, all five participants indicated that the usefulness of existing forecasting was limited by inaccuracy, and that more accurate forecasts would be useful in minimizing costs. This is consistent with the literature from the technology acceptancy model in that those are all components that drive perceived usefulness and there decreases the overall intention to use the system. Three participants indicated that management did not enter expert forecasts into databases for later comparison with actual yields. The IT manager, did not contribute to this major finding because he based predictions solely on data rather than expert opinions. The field manager provided inconsistent data stating that a process was utilized to check forecasts based on expert opinions for accuracy. The field manager did not state that the results of accuracy checks were documented or aggregated, however, or that forecasting processes were adjusted on the basis of historical accuracy.

The sales manager and the controller indicated that the majority of their yields were sold according to contract pricing, a major finding discussed in more detail in Phase 2. Lastly, all five participants agreed that the data they collected did not provide a sound basis for decision-making, either because the data were irrelevant to the decisions needing to be made, or because other data needed to supplement them were not being collected. This finding supports the idea from social technical systems theory that change needs to be made in both the socials aspects though changes to the belief in the value of the data and technical aspects in the way the data is processed and presented.

4.2. Phase 2: Predictive and Descriptive Analytics

The findings presented in this section are organized by participant. The discussion of the findings from each participant is organized by major finding. Within the discussion of each major finding, direct quotations from the data are presented as evidence.

4.2.1. Sales Manager

Table 7: Phase 2 Sales Manager Summary of Responses

Sales Manager	
What would you like to forecast?	Supply(yield) and demand (customer orders). Supply quality and the factors involved would be useful too. Yield would be more useful separated by quality and sizes.
How happy are you with your forecasting ability?	It is very poor, could use significant improvement, sometimes yield can go from 75% to 50% and we don't know why.
What would you like to forecast that you currently are not forecasting?	Quality and sizing could use improvement. The biggest variable that affects us is rain, both on citrus and on stone fruit.
Why aren't you currently able to forecast those items?	Accuracy of field information is poor. Inputs are unpredictable.
What data would you like to have that you currently do not have?	Accurate field yield with sizing and quality.
What do you think could be done to make the expert opinion that you rely on be more accurate?	More user-friendly data, because right now, you're having to pull information from a lot of different spots, and then you use all of that information, and kind of mush it together to try and figure something out.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The sales manager described forecasts related to weather and product quality. Of the usefulness of more accurate weather forecasts, the sales manager said, "The biggest variable that affects us is rain . . . especially on nectarines. Then on citrus, it affects our ability to harvest." However, the sales manager expressed skepticism about the usefulness of historical weather data in forecasting future weather: "If there was a surefire way of using that [historical] information, I think it would be helpful. [Weather is] just always so unpredictable." The sales manager used a hypothetical example to express his belief that useful quality forecasts were impossible to make because unknown factors had drastic effects. He based the example on his experience that approximately 75% of a peach harvest was typically usable: "All of a sudden we're getting 50% utilization, and there's some sort of external factors that are affecting that, and it's usually pretty difficult for us to try and attribute what it is." The sales manager offered a second example of unpredictable, unknown factors rendering quality forecasts inaccurate: "When the fruit comes in, it looks fine, but then all of a sudden it stains up and then turns brown some years are worse than others for staining, but no one's really found out what actually causes it."

Major Finding 2: Pricing for a majority of the yield is contracted.

The sales manager indicated that contract pricing depends on forecasts instead of the day-to-day fluctuations that determine market pricing. The sales manager added that forecasts of production quantity and cost are used in the negotiation of contract prices as "A baseline of where you're trying to set your prices for, say your seven-year costs or your contracts that break even, plus whatever you want to make."

Major Finding 3: The information being collected does not help with decision-making.

The sales manager said of current data collection capabilities, "It's really pretty archaic in terms of the way we do things." Demand forecasts, for example, are provided by customers and are not aggregated year-over-year or checked for accuracy: "We get estimates from some of our customers. They actually provide them, but we don't have anything that actually looks at historicals in terms of, this person bought this, or that person bought this size, or anything like that."

4.2.2. Field Manager

Table 8: Phase 2 Field Manager Summary of Responses

Field Manager	
What would you like to forecast?	Supply(yield) and variety demand (customer orders). Quality.
How happy are you with your forecasting ability?	Room for improvement.
What would you like to forecast that you currently are not forecasting?	Using historical data to estimate crop yields. Neighbor's yield. The global economic environment and having forecasts about that.
Why aren't you currently able to forecast those items?	Lack of information in the right format to be analyzed.
What data would you like to have that you currently do not have?	Accurate field yield with sizing and quality. Aggregated data from the packing facility would be gathered in a way that allows us to compare yield data and production data. A system to track field measurements to look at their historical accuracy. Citrus estimates, and then also on the tree fruit side, estimating crop yields there would be beneficial, then that would help us analyze our strategies for thinning purposes.
What do you think could be done to make the expert opinion that you rely on be more accurate?	Expertise varies between field checker; they rely significantly on expertise and the level of expertise varies widely

Major Finding 1: Useful forecasts are perceived as impossible to make.

The field manager described crop yield forecasts as potentially useful if greater accuracy could be attained: "Like citrus estimates, and then also on tree fruit side, estimating crop yields there would be beneficial. Then that would help us analyze our strategies for thinning purposes." More accurately estimating crop yields would contribute to increased efficiency in inputs such as pruning. The field manager said: "Pruning could play a part of it, or cultural practices, depending on your total crop estimates. So maybe we'd lessen our crop, or inputs in, in terms of pruning, or mechanical pruning, as a result of a lighter crop." The field manager stated that current crop yield forecasts were based on expert opinion.

While historical data on factors such as weather had the potential to be useful in improving forecasts, the field manager described those data as "tedious to capture." He also expressed the perception that expert opinions were often based on judgments derived from knowledge and experience, and that making such opinions more useful would be difficult or impossible because "There are situations that definitely are ... you just kind of lean on your expertise in overall what you've seen historically, and you manage through it."

Major Finding 2: Long lead times between changing an input and realizing the effects of the change are problematic

The field manager described input changes with long lead times related to crop yields as unreliable because of the unpredictability of the weather. The field manager stated: "Estimating crop yields would be beneficial, then that would help us analyze our strategies for thinning purposes." More accurate crop yield estimates would also contribute to the quality of information provided to marketers: "Say we're on an off year, and we're able to see that ahead of time and forecast that and give the marketing team a heads-up. And then they can forecast their marketing strategies accordingly." The field manager added that the potential for inputs with long lead times to be invalidated by intervening events precluded “viable estimates moving forward to give the marketing side a better gauge of what the crop load looks like.” The unreliability of crop yield estimates with long lead times prevented optimization of cultural practices, the field manager said, adding that if long-range predictions were more reliable, “We'd lessen our crop, or inputs in, in terms of pruning, or mechanical pruning as a result of a lighter crop. Or we enhance that, the cultural practice, if we know it's going to be a bumper crop.”

Major Finding 3: The information being collected does not help with decision-making.

The field manager affirmed that data on weather, yield, demand, quality, and labor costs needs to be aggregated year-over-year to make decisions that would maximize efficiency, but he added “The one thing that we currently do not have is the ability to aggregate yearly data and create dashboards that produce analytical trends.” The field manager also stated in the same response, “If we could create tables or dashboards that produce aggregated annual yield data to base our determinations off of, that would be an ideal scenario.” In providing an example of why aggregated, yearly data on factors such as weather and yield were needed for decision-making, the field manager said, “If we can look at historicals, and similar degree days or temperature correspondence, and see how that relates to, let's say, 2012, if that was a similar year, we could see how that affected our commodities.”

4.2.3. IT Manager

Table 9: Phase 2 IT Manager Summary of Responses

IT Manager	
What would you like to forecast?	Supply(yield) and demand (customer orders).
How happy are you with your forecasting ability?	Works fairly well, but the expert opinion used can vary widely in accuracy. Plus it seems to be used very reactive instead of proactive. We do have a database that collects and stores data of all of the activity done to a particular field every year.
What would you like to forecast that you currently are not forecasting?	I think where we're doing it, we're doing a pretty good job. I do know if other parts of the country have severe weather or other impact on their crop quality or yield, but it is not stored in a database.
Why aren't you currently able to forecast those items?	Lack of information in the right format to be analyzed.
What data would you like to have that you currently do not have?	None. You can know what you're going to be packing and storing without overflowing or without running short of any particular product.
What do you think could be done to make the expert opinion that you rely on be more accurate?	You wouldn't want to rely on just one expert opinion, but rather a consensus of experts, an average opinion across whatever that question may be.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The IT manager said of current data collection and forecasting practices, "It works fairly well, but we're not capturing every piece of data that we could. Some of those things are expert opinion only, or we're getting the after effect of those commodity price changes, more reactive than proactive." Useful forecasting of commodity prices was impossible because prices were drastically affected by unpredictable events. The IT manager stated: “If, for example, there's a hurricane in the Florida orange crop or the Georgia peach crop is damaged, of course, that does have a pretty big impact on our commodity prices.” The IT manager said of forecasting commodity prices: “We can predict some change based on those occurrences [e.g., hurricanes], but it's not tracked in any system currently that I know of.”

Major Finding 2: Long lead times between changing an input and realizing the effects of the change are problematic.

The IT manager cited unpredictable, adverse events as threats to the reliability of input changes with long lead times. He reported that forecasts of commodity prices were particularly vulnerable to falsification as a result of events such as natural disasters: “[Adverse events like hurricanes are] going to have a rippling effect on that commodity price in general, but it is usually delayed. It will take a week or two for the impact to be felt.” As a result, the IT manager stated, “It's more of an expert opinion, and we'll see the effects in looking at the market and seeing commodity prices as they get adjusted. we're getting the after effect of those changes, more reactive than proactive.”

4.2.4. Controller

Table 10: Phase 2 Controller Summary of Responses

Controller	
Would you like to forecast?	Supply(yield) and demand (customer orders). A weekly forecast, or projection of what will be picked in the following week would be helpful for scheduling purposes.
How happy are you with your forecasting ability?	Forecasting with financials is done fairly well, but the non-financial forecasting is fairly poor due to lack of accuracy in the metrics.
What would you like to forecast that you currently are not forecasting?	I have what I need. Numbers on what you usually get from each variety or each tree could help project how much good food would actually come into the packing house.
Why aren't you currently able to forecast those items?	When pricing has an issue, they have to go back to when they do thinning, which is too far ahead of the game. If you look at the reports, and I have too many times, year by year the same block could change drastically. Forecasting quantities, from everything that I've worked with, just doesn't seem to be very accurate, it is just a hit and miss game.
What data would you like to have that you currently do not have?	Right now it's a manual tag that they fill in for each block, and each contractor, and each category or phase that they do. But this is only stored on paper. It does not get put into a database. .
What do you think could be done to make the expert opinion that you rely on be more accurate?	I don't use expert opinion.

Major Finding 1: Useful forecasts are perceived as impossible to make.

The controller described accurate forecasts of crop yields as desirable for predicting labor demands in advance. Existing forecasts are of limited use. The controller said: "The projection or the estimate of what might be, [field managers] won't react to it.

They won't have the right staffing time to deal with it, because it could be way off, based on history." In the absence of useful forecasts, the controller stated, "[Field managers] react almost on a day-to-day basis of going out there and taking a look and saying, 'Okay, this one's ready. Let's pick this today.'" However, the controller believed that crop yields were influenced by too many variables for useful predictions to be possible: "Forecast as far as quantities go, I've been watching this thing for years and the volumes change so drastically so quickly. I mean, you could have a block one year that's doing great, and the next year, all of a sudden, and for sometimes unknown reasons, there's nothing. So forecasting quantities from everything that I've worked with just doesn't seem to be very accurate, would be just a hit-and-miss game."

Major Finding 2: Long lead times between changing an input and realizing the effects of the change are problematic.

The controller described the unpredictability of crop yields and corresponding customer demands as limiting the reliability of input changes with long lead times. The controller stated that accurate forecasts of customer demand would affect pruning because, "Thinning helps create a different-size fruit. If the pricing structure is based on larger versus smaller fruits, and you want larger fruit, you're going to have less fruit on a tree, but you'll have larger fruit." The controller said that in order to make optimal decisions about thinning, "You want to anticipate a higher price for larger fruit, which isn't always accurate." Long-range customer demand predictions were unreliable as inputs on which to base agricultural practices, the controller said, because they are made "too far ahead of the game."

Major Finding 3: The information being collected does not help with decision-making.

In providing an example of a decision-making process for which the data being collected were not useful, the controller stated, “Is additional pruning cost-warranted? Are you spending more money to get bigger fruit than you would get if you had less pruning [and were] generating smaller fruit, and would that equate to more volume and more sales?“ The controller stated, “analytics could help show what we’ve done in the past and if it’s valid or not.” The controller added that current forecasting processes were conducted without historical data on previous forecasts and outcomes, and that as a result, “There is really nothing we can change. The forecasts are for the citrus that is updated weekly, but it doesn’t affect anything. it just remains a number until the season is over.”

4.2.5. General Manager

Table 11: Phase 2 General Manager Summary of Responses

General Manager	
What would you like to forecast?	Supply (yield) and variety demand (customer orders). Quality. If we know ahead of time on the demand side that there's going to be a large demand for overall volume, then maybe we don't finish heavy on a stone fruit situation.
How happy are you with your forecasting ability?	Mostly, but it's accuracy heavily relies on expertise to interpret.
What would you like to forecast that you currently are not forecasting?	A better understating of how to forecast the demand market would be useful. You have to know if you're going to be in a short water supply situation, what blocks you may choose not to farm. We get it through industry groups today, with a bit of a jaundiced eye, not trusting that we're getting full truth on the information that is shared. It would help if we knew accurately what other people were doing and volume. Historically, we anticipate an increase on packing material costs every year of 3 to 12%. We throw 6% out as an average. It is affected by the customers that we choose to do business with, be it a Walmart or be it a high-end retailer who has to have his own special packaging, which is going to cost more, that all has to be factored in, yes. If we could map out three, four weeks in advance what the market is going to do, we pretty well know what our supply availability is, whether we choose on citrus to harvest it then or wait, would give us some opportunity to maybe maximize the return to the farm stone fruit.
Why aren't you currently able to forecast those items?	Lack of reliable information. Market is very volatile.
What data would you like to have that you currently do not have?	Accurate field yield with sizing and quality.
What do you think could be done to make the expert	Better information about the variables in the forecasting would allow for better expert opinion interpretation.

opinion that you rely on be more accurate?	

Major Finding 1: Useful forecasts are perceived as impossible to make.

The general manager described weather data as critical in forecasting crop yields and quality. However, he expressed the perception that weather was impossible to predict with the degree of accuracy necessary to make useful forecasts about its effects: "Weather is one variable we have no control over. We work from history on anticipating freeze periods on citrus, hail periods on stone fruit, just never knowing exactly what's going to happen." The general manager added, "Forecasting weather is really a guess, so I don't bank much on whether you react to [the forecast]."

Major Finding 2: Long lead times between changing an input and realizing the effects of the change are problematic.

The general manager said of the value of accurate predictions with long lead times: "If we could map out three, four weeks in advance what the market is going to do. [it] would give us some opportunity to maybe maximize the return to the farm." The general manager stated that if predictions about demand could be made accurately, decisions about pruning and harvest timing could be optimized. Of pruning decisions, the general manager said, "If we believe that there's going to be a big demand on citrus for medium to larger size fruit, we don't thin citrus at all." The general manager stated of the effect of forecasts on harvest timing, "It may mean that we've got to plan our harvest a little bit later to try to gain size on the fruit." The general manager said that as a consequence of the unreliability of long-term demand forecasts, “We're just kind of riding the market and not knowing what the outcome is until we get to the end of the season.”

Major Finding 3: Pricing for a majority of the yield is contracted.

The general manager estimated that 70% of his firm’s products were sold at prices contracted with individual customers in advance. He added that the benefit of contracted prices for growers was that it “leaves us in a pretty favorable position in a normal crop volume year to better forecast our outcome versus those that might only be 30% contracted playing the open market. That's very risky.” Thus, contracted prices protected growers against the limited accuracy of long-range demand forecasts of the kind discussed in relation to Major Finding 2. The general manager reinforced this interpretation by stating in another part of the same response in relation to market pricing that “we really have to take a look at what percentage of our volume is in that classification and what do we anticipate the market doing in getting a return back on that fruit.” The general manager added, “We've got the fixed pricing in place to be able to anticipate where it's going to go, as long as we don't see prices move off of contract.”

Major Finding 4: The information being collected does not help with decision-making.

Accurate demand forecasting with sufficient lead time is not available, but is needed for effective decision-making, the general manager said, because “It would have an effect on what you're trying to do, as far as if it comes at a time where you're able to adjust your crop volume.” Decision-making related to the economic environment is impeded by the unreliability of information about competitors' yields. The general manager said: "We get [information about competitors' crop yields] through industry groups today, with a bit of a jaundiced eye, not trusting that we're getting full truth on the information that is shared." The general manager stated that more accurate information about competitors' yields would be valuable in decision-making because, "If we knew accurately what other people were doing and volume, if everybody in the area was finding that they're harvesting more than what was forecast, it may affect what we do as far as selling the product."

The general manager indicated that accurate, block-by-block data about crop yields was needed for "deciding whether a block is going to continue to be farmed or going to have to be replaced." Crop yields were not systematically forecasted at a block-by-block level of granularity. Instead, forecasts were conducted on an as-needed basis when the profitability of farming specific blocks appeared doubtful. The general manager stated: "We look back and we take a look at the history and say, 'Okay, this block the last few years has not returned the dollars back to the farm." Based on that informal analysis, the general manager said, "we would make a decision whether to pull [the block] or keep farming it." The general manager expressed the perception that information currently being collected could only be used to make forecasts that were, at best, "rough guidelines. It's not anything that I feel is accurate enough to build costing models."

4.2.6. Phase 2 Cross-Participant Comparisons and Summary

All five participants expressed their perception that the forecasts they would find most useful were impossible to make, either because the necessary modeling was prohibitively complex or because the necessary degree of data accuracy and granularity was unattainable. This idea is supported from the literature on saliency that puts forth the idea that the forecasts from models are not believed or considered real by managers. Four out of five participants indicated that long lead times between changes to inputs and realizing the effects of those changes often rendered the input change useless as a basis for decision-making. As the lead time between predictions and their expected effects increased, the potential for unanticipated conditions to intervene during the lead time also increased. Input changes with long lead times were therefore considered unreliable which is supported by the literature on data architecture that the data must be processed into an actionable form of information. The fifth participant, the sales manager, did not address this major finding, either to support or challenge it.

The sales manager and general manager indicated that contracted prices were related to forecasts in two ways. First, contracted prices protected growers against harmful demand fluctuations that they were unable to forecast. Second, growers negotiated contract prices on the basis of their production and packing cost forecasts to ensure that those costs were recouped. As in Phase 1, the field manager and the IT manager made no references to contracted prices. The controller's responses related to contract pricing were given in Phase 1. Consistent with Phase 1 responses, all five participants indicated that the data they collected did not provide a sound basis for decision-making, either because the data were irrelevant to the decisions needing to be made, or because other data needed to supplement them were not being collected. This is evidence of a data authority issue where the data being collected does not map to what information would be valuable for decision making.

4.3. Phase 1-2 Analysis and Model Development for Phase 3

From interviewing multiple key people within the organization in phases 1 and 2, a lack of understanding of the value of recording data became apparent. The commonality across the different functional areas and perspectives was non-financial information that is used for decision making isn't codified into a data warehouse in a way that models and dashboards could be derived to help move the organization from descriptive to predictive analytics. From the interviews of the key individuals it became evident that only one person valued the collective data overall picture, that being the general manager. This provides a problem because the function area mangers must have buy-in on the value of codifying and recording the information in a meaningful relational database in order for the organization to derive value from it. In order to create this saliency, in phase 3 of the interviews we presented the interviewees with a blueprint for a predictive model that could help determine correlation and causation for the key decision points in their business processes.

In this section we present a model for the factors that affect yield and profitability. When interacting with the interviewees in phase three, the following table was used to structure the interaction. I first proposed a data item to them, explained how that item could be collect and stored, and how that item could help make forecasts. For example, I said it seems that at the block level, historical weather data might be useful. This data could be obtained from localized IoT sensors and automatically stored in their ERP system. Because weather forecasts are for up to three weeks, a dashboard could be constructed to show forecasted yields for the next three weeks.

Table 12: Possible Variables and Why They Might be Useful

New information	How to collect and store	Predictive use
Field Forecasting [expert opinion].	Record expert opinion on yield and quality into ERP.	Real time dashboard and end of season correlation evaluating variance on expert opinion vs actuals.
Block level weather historical data.	Weather service or localized IOT sensors to new ERP plugin database.	Dashboard with 3 weeks of forecasts.
Pruning and Water/ Field Management (by block)	Block level recording into ERP plugin. Need some way to measure pruning (density of what is left, etc.). Water use and availability.	End of season correlation modeling.
Industry Environment (market supply).	Regional weather from major competing growing markets by week for historical comparisons in data warehouse.	Real time weather forecasts for the same regions building into dashboard with 3 weeks of rolling forecasts.
Industry Environment (market demand).	Economic indicators of consumer behavior. Some indicators are unemployment, consumer confidence, spending on grocery items, historical sales.	End of season modeling resulting in the building of real time dashboard.

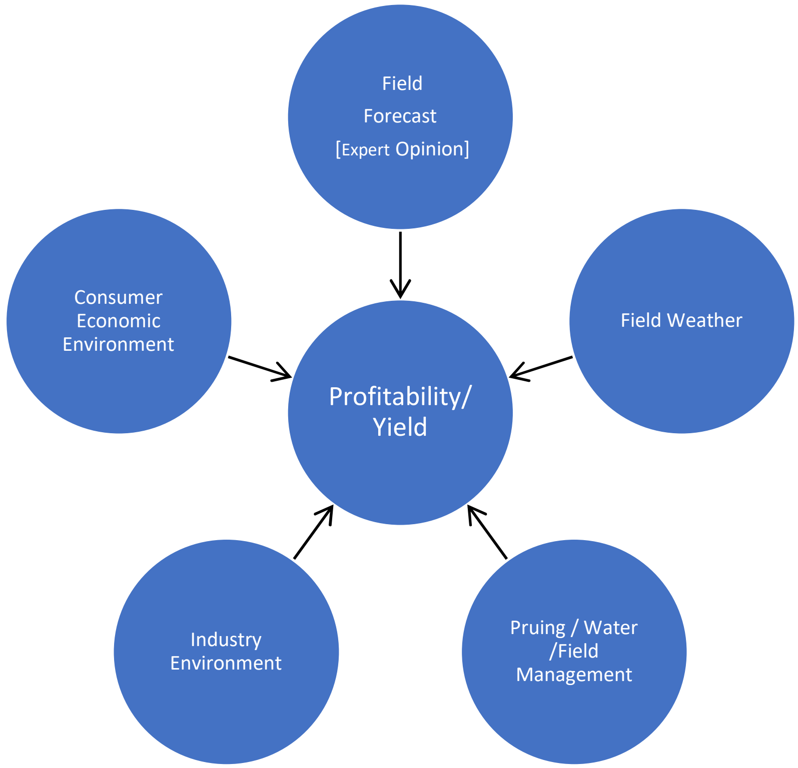

Figure 4 :Factor Model of Proposed Analytics

Survey of Proposed Analytics

A brief survey was conducted after the calls to determine rank order and perceived difficulty to implement after some familiarity with the modules in Table 12 and Figure 4 was established.

Table 13: Ease of Implementation on 1-7 Scale

(1 Being Extremely Difficult and 7 Being Extremely Easy)

	Field	GM	Controller	Sales	IT	Median	Average
Block level weather historical data	4	6	5	2	4	4	4.2
Pruning and Water/ Field Management by block	4.5	5	6	2	6	5	4.7
Industry Environment (market supply)	6.5	6	2	4	3	4	4.3
Industry Environment (market demand)	6	2	3	4	3	3	3.6
Field Forecasting [expert opinion]	5	4	5	4	5	5	4.6

Table 14: Most Valuable to Implement Ranking

(Rank Ordered 1-5, 1 Being Most Valuable and 5 Being Least Valuable)

	Field	GM	Controller	Sales	IT	Median	Average
Block level weather historical data	3	5	5	5	5	5	4.6
Pruning and Water/ Field Management by block	1	1	1	4	1	1	1.6
Industry Environment (market supply)	5	2	3	3	3	3	3.2
Industry Environment (market demand)	4	3	4	2	4	4	3.4
Field Forecasting [expert opinion]	2	4	2	1	2	2	2.2

4.4. Phase 3 Results: Plan to Prescriptive and Cognitive Analytics

The findings presented in this section are organized by participant. The discussion of the findings from each participant is organized by major finding. Within the discussion of each major finding, direct quotations from the data are presented as evidence.

4.4.1. Sales Manager

Table 15: Phase 3 Sales Manager Summarized Table of Responses

Sales Manager	
Field Forecasts [expert opinion].	Yeah, that definitely would be valuable. The way it's done now is, it's more of a manual process.
Block level weather historical data.	Yeah. One of the biggest factors associated with weather affecting the fruit would be like a move. We can move the fruit a day forward or a day back or a few days forward or few days back in terms of harvest.
Pruning and Water/ Field Management by block.	Yeah. Like you said, a lot of its just expert opinion and opinion and historical information based on the past. What they think works, and what they think doesn't work. But it's not as intricate as this would suggest.
Industry Environment (market supply).	Yeah. Like an example, small changes in supply can have dramatic influences on prices. So, for example, I think four or five years ago, South Carolina froze because they got cold weather. And so it froze the bloom on the peaches. And in terms of total peach supply in the United States, they only represent 10 to 15% of the total supply. But the pricing changes as a result of that 10 or 15% being out of the market, was maybe 25 to 30%.
Industry Environment (market demand).	Yeah. Again, it would change the way you're pricing things, if you can anticipate higher demand, and it'd probably change the packing. But it'd definitely affect your pricing due to so much uncertainty as far as not knowing what a customer is going to take.

Major Finding 1: Managers do not know what is possible.

The sales manager expressed uncertainty about if the data points of historical weather existed or could be incorporated into forecasting. In speaking of data about historical weather, the sales manager stated, “I don't think anyone has that information readily available now. I don't think there's anyone to say, ‘Yeah, we look at it and things are going to adjust’. no one does it.” The sales manager believed that historical weather data would need to be accumulated within the company over a long period of time before it could be usefully applied in forecasting: “I don't think you'd be able to do it on the first year, but I think as you continue to get data and accumulate things and see how the weather actually does affect the tree fruit in different blocks, [you could].” the sales manager also suggested that new analytics methods would need to be developed before historical weather could be used, if it were available: “It may be useful, if you guys can find a way to do it.”

Major Finding 2: The results of extra effort are not valued.

The sales manager acknowledged that forecasting pruning by field block is complex, and he believed that the current system of relying on expert opinion was adequate. He indicated that analytic forecasting was excessively intricate for making decisions about pruning: “A lot of it’s just expert opinion and historical information based on the past. What they think works, and what they think doesn't work. But it's not as intricate as this [proposed model] would suggest.”

Major Finding 3: Managers anticipate barriers to the change to new methods.

The sales manager expected that implementing an application to facilitate new modeling methods would encounter a moderate-to-high barrier to effecting the change. He distinguished between the change-management barrier of learning how to use new technology and the challenge of understanding the limitations of the forecasts to avoid overreliance on them, saying of the technology: “If we're trying to implement that, I feel like it probably would be on the easier side of things.” However, the sales manager believed that significant experience in the produce industry would be needed to contextualize and understand forecasts: “You need to have that industry knowledge to know exactly what you're looking at, because I think numbers, especially in produce, can get skewed really easily.”

4.4.2. Field Manager

Table 16: Phase 3 Field Manager Summary of Responses

Field Manager	
Field Forecasts [expert opinion].	Yes, for sure. And there's also new technology that actually will go in and I would think they're using some of... I don't know if it's got to be more enhanced in NDVI or something, where they go in and actually image the field and they're able to do forecasting that way too. But we've never utilized that technology yet.
Block level weather historical data.	Yes, but we would just have to have sensors available through the field, and how that is communicated back to a central location would probably be the biggest logistical concern.
Pruning and Water/ Field Management by block.	Yeah. Because we could technically get down into our pruning strategies by block and have that on a dashboard or something and then be able to correlate that to yield or versus the weather and what transpired that could have actually had an effect on yield or quality.
Industry Environment (market supply).	Yes. Because let's say hypothetically, Georgia, they have a small crop this year. So that's going to influence how we probably go to market and market a little bit differently, knowing that they're going to come up short or whatever the variable is.
Industry Environment (market demand).	Not really. It depends on how early you would have that data available. We would need 5 -6 months to make it actionable.

Major Finding 1: Managers do not know what is possible.

The field manager expressed the belief that gathering data about weather and comparing it to historical data at the level of the field was feasible, saying: “We would just have to have sensors available through the field, and how that is communicated back to a central location would probably be the biggest logistical concern. But I think it's achievable for sure.” However, the field manager did not believe that it was possible to integrate weather and market demand data to make predictions with enough lead-time to influence decision-making: “To make it actionable, we would have needed consumer data probably to implement anything that we would do differently for the citrus, that will be starting harvest in November, December … I'd say six months’ lead time.”

Major Finding 2: The perceived usefulness and ease of use of analytics are weak.

The field manager described a method of data collection that he perceived as having the potential to be useful in the future: “There's now new technology that actually will go in and actually image the field, and they're able to do forecasting that way.” However, the field manager doubted the usefulness of the technology in its current state because he perceived it as relatively untested and undeveloped: “We've never utilized that technology yet. It's still in its infancy stage.”

4.4.3. IT Manager

Table 17: Phase 3 IT Manager Summary of Responses

IT Manager	
Field Forecasts [expert opinion].	I think so, because it would increase the reliability of that information in the future when you need to rely on the forecast again.
Block level weather historical data.	No. I can't imagine that the sensor level data would be all that valuable, or I should say I can't imagine that it would be more valuable than weather service data, just because weather isn't that localized. You're going to have a weather system that's going to affect everything in a geography.
Pruning and Water/ Field Management by block.	Yep. Application of different chemicals, irrigation models may be right, all those different things. We do have access to the information that this work was done to this ranch, on this date, by these people, but it's not organized right.
Industry Environment (market supply).	Sure. That affects the commodity market as a whole. If you have other weather systems and other geographies, I know there have been cases where entire crops have been lost because of hail, or bugs, or what have you.
Industry Environment (market demand).	Yeah. It affects demand and pricing obviously. I think the COVID epidemic is a great indicator of that type of thing. Right? Where restaurant demand has changed quite a bit, so we might not be selling as much of our product to restaurants because people aren't eating out very much, but people are still eating the same amount of stuff.

Major Finding 1: Managers do not know what is possible.

The IT manager expressed that weather and market supply data, if integrated into one forecasting process, had the potential to yield valuable predictions: “[Weather] affects the commodity market. If you have other weather systems in other geographies, I know there have been cases where entire crops have been lost because of hail, or bugs, or what have you. That affects the market.” However, the IT manager expressed skepticism about the feasibility of obtaining sufficiently dependable data: “I guess the question is, do you track that data and correlate it, build it into your model? Those things are generally pretty hard to predict, and they're random."

Major Finding 2: The results of extra effort are not valued.

The IT manager believed that collecting weather data over time would be useful: "I think tracking [weather] would be helpful, because then you could make the correlation between yield quality." However, the IT manager doubted that the effort of collecting weather data through sensors at the level of the field would bring significant returns: "I can't imagine that the sensor level data would be all that valuable, or I should say I can't imagine that it would be more valuable than weather service data, just because weather isn't that localized." He added that high-level weather data would be adequate for forecasting purposes: "Fields that are in close proximity, you're probably going to experience very similar effects. I would think that doing it at the high level would be good enough. Tracking at a high level is probably sufficient."

Major Finding 3: Managers anticipate barriers to the change to new methods.

The IT manager described two perceived barriers to the change to new forecasting methods. The first was resistance on the part of employees who were more comfortable with familiar methods: "I think it would be an issue short term, just because in general, people are somewhat skeptical and resistant to change." the IT manager added that he expected this barrier would be overcome when employees observed the utility of the new system: "I think it would be easy for them to get behind once they see it makes their job better or the product overall better."

The second potential barrier to managing the change to new forecasting methods was the need to change at the same time how data were collected and stored, the IT manager said. Of the potential usefulness of data on field management, the IT manager stated, “I agree that keeping a history of it in a way that is easily accessible and can be related to other data points would be helpful.” The data currently available do not approach this standard, however: “We do have access to the information that this work was done to this ranch, on this date, by these people, but you can't ask the system, ‘Show me everything that's happened to this piece of land.’” The reason the data was collected and stored in this way was that its purpose was billing rather than forecasting: “It's all done based on the billing aspect of it, not really the land management aspect of it.”

Major Finding 4: The perceived usefulness and ease of use of analytics are weak.

In describing the most useful modules, the IT manager stated: “I think probably the weather and the field management give you the most granular information.” However, the IT manager expressed skepticism of the usefulness of modules related to weather and markets: “Everything else is, we talked about markets and big weather and disasters and stuff, it's very slow moving.” He distinguished between local weather and field management modules versus other proposed modules in expressing the perception that the latter related to factors that growers could not control, and which were therefore not useful to track: “I think your yields, it's something that you can control. You can't control all these other market indicators, but you can certainly control what you're doing with your own product.”

4.4.4. Controller

Table 18: Phase 3 Controller Summary of Responses

Controller	
Field Forecasts [expert opinion].	Yes. It would provide value to say where they start with and where we end up, and what the criteria is they use to see how accurate their projections are and why.
Block level weather historical data.	The weather information would have some value, but everything on the field is more long-term than current. So, having current information, it would have to be exact, and weather it just isn't the same from period to period. It would just give us some information that could give us a trend of how things yield based on types of weather patterns, but that's not all inclusive. So, I think it would have some benefit, but I'm not sure how much.
Pruning and Water/ Field Management by block.	Yes. Well, actually we do have the information of what they ... we have all the details of what they prune by tree. But yes, if we have a lot of good information, because we're constantly trying to determine the right amount. Not sure how well they use the historical data though.
Industry Environment (market supply).	Possibly. The only time we can react to somebody else's weather issues is if it's extreme, and we know that something's going to happen.
Industry Environment (market demand).	I don't know. The problem with fruit is that it's a permanent planting. You're not going to change anything from economic indicators. The only thing you might change a little might be size. But you really can't change anything. It's locked in, what you're going to have.

Major Finding 1: Managers do not know what is possible.

The controller did not believe that a module for forecasting watering by block was possible because of the number of unpredictable variables involved. In expressing this perception, the controller said: “Watering is tough because, water, [field managers] just do as needed. Depends on weather. Depends on dryness. Depends on rain. From everything I know on water, it's really just as needed. They water as needed." The controller believed that the complexity and unpredictability of factors affecting watering made expert opinions more valuable than analytics: "They know the water. Today could be different than tomorrow if it rains, because it's going to change."

Major Finding 2: The results of extra effort are not valued.

The controller believed that the results of the extra efforts needed to collect and analyze weather and market demand data would not yield a sufficient return to make them worthwhile. Of the limited value of weather data, the controller stated, "Weather just isn't the same from period to period. It would just give us some information that could give us a trend of how things yield, based on types of weather patterns, but that's not all inclusive." The controller indicated that weather data might have some value, but that projections derived from it were unlikely to be dependable enough to improve decision-making: "Everything on the field is more long-term than current. So, having current information, it would have to be exact, and I think it would have some benefit, but I'm not sure how much."

The controller also doubted that market demand projections with sufficient lead time would repay the effort of making them: "The problem with fruit is that it's a permanent planting. You're not going to change anything from economic indicators. It's locked in, what you're going to have. You have to change your planting structure, which takes years." The controller specified that his doubts about the value of efforts to predict markets were primarily related to decision-making about production: "The only thing not indicated it would affect would be price. If you know that there's going to be a shortage somewhere else, you could probably increase your price, but you can't change anything to do with the production."

Major Finding 3: The perceived usefulness and ease of use of analytics are weak.

The controller was asked during the Phase 3 interview if tracking the weather service data and learning, for example, that a hurricane was three weeks away could usefully influence decision-making related to shipping and packing. The controller said that the prediction would not be useful, answering, "You know, it can't. The fruit has to be picked when it's picked, when it's ready. You can't pick it early because there's a hurricane coming, because it wouldn't be ripe enough. It wouldn't be ready."

4.4.5. General Manager

Table 19: Phase 3 General Manager Summary of Responses

General Manager	
Field Forecasts [expert opinion].	Absolutely. Yes. Currently we aren't following up right with it. Measurement or accountability is important as well, because your information is only as good as what's provided. And so yes, that has to be done.
Block level weather historical data.	Sure. Supply and quality are the two major variables affected and so there's a difference in citrus and stone fruit, but in either case it really is supplying quality. And so that information is very important.
Pruning and Water/ Field Management by block.	Sure. Again, it has an impact on supply and quality. And so you need to take a look at what your input variables are and what differences may be between blocks or decisions made to prune at certain times or thinned to a certain level, on the stone fruit and also on the citrus level of pruning, done to the trees and what the resulting quality of fruit will be. So yes, very important.
Industry Environment (market supply).	Yes. If there's any other supply coming in at the same time period, what is the weather impact? It's an impact on supply. Supply and demand is what drives fresh produce market and those are important variables that we have to look at.
Industry Environment (market demand).	Definitely a plus. There's a higher volume of business that's contracted today, and so knowing what the consumer trends are going into it helps us in the effort of pricing the contracts and in anticipating with open market. If it looks like it's going to be slow in the open market, you might commit to the contracted business in a higher volume.

Major Finding 1: Managers anticipate barriers to the change to new methods.

The barrier the general manager anticipated to changing to new methods was that staff might resist the shift to a paradigm when they had no prior experience of its value. Of the current forecasting process, the general manager stated, "It's nothing that we use as a dashboard predictive in processing. It's anecdotal, it's in meetings that we discuss when it's winter-time rain or freeze, in the summer-time it's heat." The general manager said managers' perception of the value of the paradigm would be "really driven by the value and benefit of the results that come from that tool."

If managers were not sufficiently impressed with the value of the new tool, then, "It goes back to trusting people with experience and through communication with field and sales and operations: 'What makes sense? What are we going to do?' That's how we operate today on a day-by-day basis." The most significant barrier the general manager anticipated to demonstrating the value of new methods within a sufficiently short span of time was the firm's current lack of readiness to implement changes and the necessity of waiting to confirm predictive accuracy until a considerable investments of time, effort, and resources had been made: "I think it's a follow-up stage to compare forecast to actual, I don't know that we have an automated mechanism in place nor a person assigned to really stay on top of that."

Major Finding 2: The perceived usefulness and ease of use of analytics are weak.

The general manager indicated that the expected difficulty of using a new forecasting model might be prohibitive to implementing one. The general manager said the difficulty of transferring existing spreadsheet-based data into a format conducive to analytics would present a threshold challenge related to difficulty of use: "Everybody's taxed on time to sit down and set up the models or collect the data to put it in reports." The general manager acknowledged that the current, Excel-driven data collection was inefficient, saying, "We don't have a vehicle today other than people using Excel and spreadsheets. And that does take a fair amount of time, especially if you have to create an Excel spreadsheet model for each report that you need."

As discussed in the previous major finding, the general manager perceived creating and using a new system as representing a significant divergence from traditional methods in which, “You're working from years of experience, and that tends to be what we do: ‘Okay, we got these variables and so the decision that we're going to make is based on what we know today being X, Y and Z.’” The difficulties current personnel are likely to encounter in transitioning to a new system mean that a significant investment of resources would be necessary. The general manager suggested that the firm would need “to go out and hire additional people to build those models and do the data entry.”

Phase 3 Cross-Participant Comparisons and Summary

Four out of five participants provided responses indicating that managers did not know what was possible. This is consistent with the literature on saliency that requires an understanding of what is being measured before those metrics can be used for more advanced analytics. Gaps in knowledge were related to the ability of forecasts with long lead times to be useful in decision-making and to the possibility of modeling processes that involved unpredictable variables. The general manager did not contribute to this major finding but did not contradict it.

The sales manager, IT manager, and controller expressed the perception that the results of efforts to implement new systems would not be valuable. The sales manager believed the intricacy of the proposed model exceeded the complexity of the predictive task. The IT manager expressed that weather data at the level of the field would be unnecessarily granular and would not repay the effort of collecting and analyzing it. The controller expected that predictions with long lead times would be too unreliable for their influence on decision-making to repay the effort of making them. The field manager did not contribute to this major finding but did not contradict it. The general manager provided conflicting data by indicating that he perceived all of the proposed modules as having high potential value. The major constructs and contributing factors for this major finding are consistent with the factors and subfactors of the technology acceptance model.

The sales manager, IT manager, and general manager anticipate barriers to making the change to new methods. The general manager and IT manager expressed that managers were likely to resist the shift to a new paradigm when they had no experience of its value, and that the system would need to demonstrate its value before managers would fully accept it. The sales manager, IT manager, and general manager all expressed the perception that transitioning to a new system would involve processes of converting data and changing procedures that would require substantial investments of time, effort, and resources to accomplish. These required changed to both the technical and the social aspects of their business process are supported by dual optimization within social technical systems theory. The field manager and controller did not contribute to this major finding but did not contradict it.

The field manager and IT manager perceived the usefulness of a new system as weak. The field manager perceived new forecasting methods as insufficiently developed to be useful in decision-making. The IT manager perceived advanced forecasting relating to weather and market supply as lacking in utility because they provided information about conditions which growers' decision-making processes were unable to influence. The general manager expressed the perception that transitioning to a new forecasting process would be too difficult for current employees and that additional employees who understood the model would need to be hired, making the transition a larger investment and a greater risk. This is consistent with the technology acceptance model that indicates that a weak intention to use is driven by lack of perceived usefulness which it itself is driven by a lack of job relevance. This finding is also consistent with the idea from TAM that a lack of voluntariness in use of the system also directly drives the intention to use.

5. SUMMARY, IMPLICATIONS AND CONCLUSIONS

The field study reveals that SunWest Fruit lies between Levels 1 and 2 in the data analytics hierarchy. The company's progress toward adopting advanced analytics stalled before adequate data collection activities from which meaningful descriptive analytics can be generated were implemented. The company is currently in a position where they have dashboards, but are unsure how to use them or even what information they contain. A deeper analysis has determined that the company does not have access to the right data in the proper format for higher level data analysis that could be used to feed a decision support system.

Furthermore, the managers perceive useful forecasts as impossible to create. They do not believe it is possible to gather information that could lead to more advanced analytics. In addition, management rarely checks the accuracy of expert forecasts for yield, which leads to inaccuracies that can approach 50% without managers having any intention to investigate the root cause. This creates significant inaccuracies in the raw data upon which any advanced analytics would be based. Follow-up questions revealed that the managers believe there is little that can be done in a timely manner to correct these inaccuracies: this belief is assumed to be responsible for their inaction.

Another issue regarding the organization's lack of belief in the need for advanced analytics is that the pricing for a majority of the yield is contracted, so prices are fixed before the season begins. Little evidence is generated from key performance indicators (often profit) to recognize a value in the increased data collection and management; therefore, the information being collected is perceived as not helpful for the decision-making process. Department managers were also found to believe that useful forecasts are impossible to make. This has been shown to occur primarily because the long lead times between changing an input and realizing the effects of the change reduce the perceivable benefits of the extra effort.

Within the organization, departments other than the end users of the decision support systems would be responsible for collecting and codifying the data. This has led managers to anticipate significant barriers in managing the advanced data collection and thus failure to undertake the change management process. These issues suggest that the perceived usefulness and ease of implementation of the advanced analytics are fairly weak.

The most important finding of this study is the importance of co-learning. Managers will not ask for help with a problem if they do not think the problem is solvable. Prior studies have shown the most effective way to interact is by asking for help with a problem, not asking for data (Shao & St. Louis, 2019); but this will not happen if managers are unaware that the problem is solvable.

The managers within this organization were not aware of the total scope of what data could be available to aid in decision making. At the same time IT was not aware of what business questions management needed help with and how more advanced data availability and analytics could increase their profitability. During the investigation phase of the field study an intervening learning phase needed to be introduced between phase two and three because a disconnect existed between the needs of the organization and the saliency of those needs. Because of this disconnect mangers believed that the problems were more difficult to solve than they actually were.

The main question that now needs to be asked by further research is whether this learning process can be accomplished without a third-party intervention. What type of business processes and procedures must be developed to build the culture of change management and co-learning into the data analytics program within an organization? Without this this change in the culture of interdepartmental interactions and co-learning, this study has shown that it is virtually impossible to realize the benefits of more advanced data analytics systems.

From previous research it was originally believed that co-learning was primarily an important process to fix change management issues within an organization, but from this research it can be inferred that it is also extremely valuable when things are going well in the organization. When there is no apparent problem within the organization the willingness to implement new procedures and data analytics processes was shown to be extremely weak. This study brings to the forefront the idea that a cultural shift within an organization needs to be made to change from a culture of good enough to a culture of striving for the most advanced form of data analytics. This being a continuous improvement process of smart business experiments to optimize the business processes of an organization.

A major contribution from the interviews in this study is that evidence is provided for the inference that if there is not an obviously apparent problem that there will be no willingness to make meaningful change within the organization. This leads to the next phase of this research stream where the research question is; What sort of process is necessary to accomplish business process optimization to drive increased profitability? To move up the data analytics hierarchy, managers have to look for opportunities to increase revenue or reduce costs. In order to accomplish this the organization needs to have processes in place to look for the data that would make this optimization possible. They must examine opportunities for change and not just investigate obvious problems.

The factors that led to a lack of willingness to change were extremely apparent within SunWest. Because of the nature of the fresh produce industry (with a few large customers and distributors) the industry is predominantly operating in a price taking model where the customers actually set the price that they are willing to pay instead of the supplier setting the price. Within the fresh product industry, since total revenue is generally fixed over the course of the year due to contract pricing, any increase in profit must be derived from the cost side of the equation. Profit equals revenue minus costs and with revenue being extremely difficult to shift costs become the main driver. Within their internal vertically integrated supply chain they have a substantial amount of fixed costs, but from the interviews it became apparent there was also a source of variable costs, mainly pruning, water, and field management. This led the managers to rethink their existing judgements on the value of advanced business data analytics once the value of recording and codifying such data became more salient. Perhaps their most interesting realization by the managers was that the data items they felt would be the most useful to them also were the data items they felt would be the easiest to obtain. This rethinking would not have occurred if co-learning had not made the benefits more salient.

5.1. Social Technical Systems, Saliency and Change Management

Responses from individuals within the organization are consistent with the social technical systems theory (Trist & Bamforth, 1951). From the social perspective, managers do not firmly grasp the possibilities of more sophisticated data analytics; from the technical perspective, IT analysts do not understand the real problem the technologies are meant to solve. This mismatch creates a stale-mate situation, where managers do not know what is possible, and IT analysts do not understand the problem.

It has become evident that unless managers understand the technology and IT workers understand the business, this mismatch will persist. This dual movement required to accomplish this process is supported by social technical systems theory. This study has found that the IT analyst role is the most valuable piece of the puzzle. To make meaningful change, IT analysts must understand the root problem and explain the value of the data to the managers before project work can be realized.

The users of the information are not asking IT analysts for new data, nor are analysts proactively suggesting improvements in data management and dashboards. This change management process must be a two-way operation to effectively implement change. Another roadblock to the change in the organization is that they are profitable. Because of this the organization as a whole is cautious about increasing complexity that could induce a failure. Without a nudge from competitors or customers who require increased trackability, there is little impetus for change.

5.2. Technology Acceptance Model

The findings of this research are also consistent with the technology acceptance model (Venkatesh & Davis, 2000). The findings support an average perceived ease of use, but a major gap exists in perceived usefulness. After education about what types of analytics are possible a survey of the managers determined that it is not seen as difficult to increase the quality of data collection, and therefore have the information for more advanced data analytics. However, more in-depth questioning discovered that the root cause was a lack of saliency in the results of the added effort; therefore, the added effort is not valued. In other words, the perceived value of the ability to provide timely, actionable information that would impact decision-making is extremely low. This is believed to be caused by the high dependency on contact pricing and the long lead time between when actions can be taken and the resulting effects, which would be evident in the bottom line. The findings suggest that a lack of saliency of the long-term effects is the root cause of this gap.

5.3. Barriers to Implementation

A surprising finding within the organization is a resistance to advanced analytical experiments. The Information Technology department was shown to be reluctant to increase complexity. It is hypothesized that this could be due to historical punishments over previously failed implementations of ideas. In recent years, the systems analyst role in the IT department has taken a backseat to the task of ensuring uptime for transactional operations. A culture of arrogance also exists among sales department managers, who believe that the IT department does not understand their needs and is therefore resistant to the introduction of new ideas. The belief that IT analysts do not understand the problem effectively creates substantial barriers to any recommendations.

Because of this tension, a fear of failure exists that is preventing the IT department from making meaningful suggestions for increasing the data analytics capacity of information systems. As such, one major finding of this research is that the culture of the organization is a primary factor in increasing its data analytics capabilities. This infers that cultivating a collaborative environment, where IT can teach domain experts what is possible and domain experts can explain their true needs to IT analysts, is necessary to allow more advanced business decisions.

5.4. Suboptimization

The design of this study allowed the environment of the organization to be held constant while the problem was examined from different perspectives within the organization. This made suboptimization extremely evident, due to the different goals of each department. While most managers cited profitability or yield as their key performance indicators, this difference in perspectives seems to create some shortsightedness when considering other managers' needs. Within the organization, data is collected by one set of departments, mainly field and packing, whereas the main information consumers are in the sales and accounting departments. Each manager seems to have a different definition of success. For example, the information technology manager valued decreased system complexity, thus ensuring greater uptime and fewer system failures. Field management departments valued optimizing yield per block to produce the most high-quality fruit possible, whereas the accounting department valued the ability to effectively track costs and calculate the cost of growing the fruit. Both the sales department and general managers valued quality metrics and costs, but since they are not part of the data generation loop, their needs are not valued by the field department, where the bulk of the additional data creation work would need to occur.

5.5. Best Practices and Recommendations

From this study, the actionable recommendation for the organization is that a problem-based discovery process be undertaken jointly by the IT department and the domain experts who manage data collection. Prior work showed that managers must ask for help in solving the root problem, not just ask for data. This finding implies that unless certain conditions are in place, more advanced analytics are impossible to implement. In particular, management must have some idea of what is possible, and IT must have some idea of what management needs. Within the organization, this lack of co-learning seems to be the most significant barrier to generating the will for a successful implementation of usable, descriptive analytics; which is a required first step before moving to predictive or prescriptive modeling. The understanding of what the data can do at higher levels of analysis is not salient within the organization and is therefore not valued.

The analysis of the Phase 1 and 2 interviews in Section 4.3 introduced a teaching element into the Phase 3 interviews. After the managers were educated in the possible inputs and outputs for more advanced analytics, the suggested data sources and/or models were seen as somewhat simple to accomplish and of value to the organization. This change in the view of analytics within the organization provides support for the hypothesis that an increase of saliency of the final output of the analytics will increase the will to perform more robust data collection practices within the organization.

5.6. Future Research

Throughout this study, many inferences into this investigation have been made regarding the root cause of the stagnation of the evolution of advanced analytics within this organization. The next step in this research stream would be to revisit the organization to investigate whether the education of what was possible that was conducted in the Phase 3 interviews meaningfully impacted the day-to-day operations of the organization, as well as how the managers take responsibility for their role in the larger data analytics ecosystem of the organization.

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APPENDIX A

TRANSCRIPT OF INTERVIEWS CONDUCTED JUNE-JULY 2020

IRB BENIGN BEHAVIORAL EXEMPT

Sales Manager:

Phase 1

Interviewer: What are your KPI (Key Performance Indicators) for your operations and what metrics help you define success?

Sales Manager: In general, for the entire organization I would say profitability and returns per acre. The two metrics that would be looked at the most closely would be the essential packaging profit and the facility. Within my own role, the KPI's would consist of the sales price, however, there are multiple variables that would account for the entire profitability. For example, you need to balance the sales price with the production per acre. You must also take into consideration that the sales price does not tell the entire story, due to different packaging that we are implementing for different things. Ultimately, there are different levels of profit margins depending on the style of packaging.

Interviewer: To confirm, you are saying that it comes down to the profit margins and the sales price?

Sales Manager: Yes.

Interviewer: What do you use to track those metrics?

Sales Manager: We will take everything back on an equivalent basis and that will give us our profit margins.

Interviewer: Do you have an enterprise management system that records all of the data for you?

Sales Manager: Yes, we use software for that. The software will input our prices while we are invoicing customers and that will go onto an equivalent basis, which is what we use for tracking in terms of profitability.

Interviewer: From that system, what kind of information is in the reports you generate?

Sales Manager: When you pack produce there are a bunch of different sizes and the reports will compare the size and the price. Ultimately, the reports will compare the prices to different customers for the same size fruit. For example, if you are examining oranges there are going to be six sizes of oranges and the reports will put all of the sales for one size into one bracket and it will compare them to one another. Then, it will put all of the oranges in a different size and compare them to one another.

Interviewer: If you find issues regarding the numbers the reports produce, are there drill down tools in place to identify the root cause of the issue that you can find within the reports?

Sales Manager: Definitely not, the software that is most commonly used in produce is called Famous Software and it is very archaic, rudimentary, and not very user friendly.

Interviewer: Regarding the data that is constantly being collected by system, is it being presented in a way that is readily available before those reports are generated for the purpose of keeping track of where you are at all points in time?

Sales Manager: No, they're not and most of the reports are custom. The basic software lacks a lot of functionality and the ability to do things with it. We have the ability to do custom reports but they are pretty expensive.

Interviewer: I recall visiting your office and noticing projectors on the walls displaying information, that information can be considered a dashboard. What kind of data was being displayed and please explain how it helps?

Sales Manager: Usually they are displaying forecasts in terms of when the harvest is coming in and what availability we currently have. These are all done in excel spreadsheets, which is probably relatively archaic considering the technologies currently available.

Interviewer: To confirm, the data is not updating in real time and you would have to update the system manually?

Sales Manager: Correct.

Interviewer: You mentioned forecasts were being displayed on the walls, what kind of forecasts?

Sales Manager: When we harvest the fruit, we harvest them in bins. Then, once the bins acquire a certain utilization, it will forecast the utilization along with the size structure that we are anticipating.

Interviewer: After you determine the real numbers, do you go back and analyze whether the forecasts were accurate?

Sales Manager: Occasionally, but it depends on the situation. For most situations we probably won't but in some circumstances we might. We do have an estimate regarding the crop for the upcoming season and at the end we will compare what our estimate was versus what we actually got.

Interviewer: When you or your team are producing those forecasts, do you rely mainly on data or expert opinion?

Sales Manager: It depends on who is doing it. Usually it is comprised of past data, however, sometimes it's expert opinion and other times it is a combination of both. Historically, a lot has been driven by expert opinion but there is a lot of value in data. I would say more data is being integrated but it is still pretty rudimentary at this point.

Interviewer: Based on the results of the forecasts that were made, have you changed the operations and taken any actions based on that data?

Sales Manager: Yes, we are using that information constantly, especially on citrus more than stone fruit. You have to manage the crop to obtain the customers supplies for a certain period of time. Thus, having an accurate forecast enables you to decide whether or not you want to harvest x amount of fruit per week or whether you want to harvest significantly more or less than that number.

Interviewer: Are there any aspects of the operation that you think analytics could help improve?

Sales Manager: I think that if better forecasting abilities were available it would be extremely beneficial since our current forecasting capabilities are quite challenging. However, one of the problems pertaining to developing forecasts is that you are only as good as the information and the data that you program into the system. Furthermore, there are a lot of moving pieces within the data of a production facility and the numbers might say one thing but in actuality it might be something else. This is where I believe the produce industry becomes very hard. There are a lot of variables where the numbers won't indicate what is actually taking place.

Interviewer: I've heard that a lot of your pricing is dictated by long term contracts. However, I've also heard that a large component of the pricing is dynamic. What external factors help determine those prices?

Sales Manager: The dynamic pricing is driven by very simple economics, such as supply and demand.

Interviewer: Are there any external factors that affect your pricing? For example, at this point in time the average consumers disposable income is substantially different because people have not been working for the past few months. Is that something that has affected pricing?

Sales Manager: I'd say the bigger factor that is driving changes right now is the fact that more people are eating at home since the food service industry shut down. Subsequently, we are seeing much more traffic in grocery stores than we saw prior to the pandemic. For example, we saw citrus sales go up between 50-100% with some of our customers.

Phase 2

Interviewer: Okay, great. Okay. So we're going to do a continuation of kind of where we left off. This is going to be looking into more of forecasting and data.

Sales Manager: Okay. Sounds good.

Interviewer: We're trying to figure out different areas that you would like to forecast or that you currently forecast.

Sales Manager: Okay.

Interviewer: To what extent do you currently forecast demand?

Sales Manager: Demand or production?

Interviewer: We can talk about both, so both demand and on the yield side. So actually, we're going to look at the customer side.

Sales Manager: Okay. We get estimates from some of our customers. They actually provide them, but we don't have anything that actually looks at historicals in terms of, this person bought this or that person bought this size or anything like that. It's really pretty archaic in terms of the way we do things. So yeah, a few customers will send us something as far as what they think they're going to sell, but the majority of them don't give us a whole lot of information, so we are kind of flying blind.

Interviewer: Okay. So then on the other side of it with the yield, is that something you're forecasting as well?

Sales Manager: Yeah, so that is something like, we have the estimates of previous years, and then we use some of the current data as far as sizing. Then you look at bin counts from prior years, and then estimate based on kind of lay those over one another to give a projection for... We have one board that does the daily and weekly, which I know you're familiar with, and then I also do one that does a week by week for the next four weeks.

Interviewer: Would keeping track of weather help in your forecast at all?

Sales Manager: I'd say it potentially could. I'd say the biggest variable that affects us is rain, both on citrus and on stone fruit. If we don't get as much during stone fruit, but it does have a pretty big effect, especially on nectarines. Then on citrus, it affects our ability to harvest. So, if there was a surefire way of using that information, I think it would be helpful. It's just always so unpredictable.

Interviewer: Does the availability of water change your planning at all?

Sales Manager: The availability of water, you said planting?

Interviewer: Planning.

Sales Manager: Oh, planning. It would have effect, I guess, what kind of crops you're trying to grow, and then whether or not we put fan jets, and we stopped flood furrow irrigating the majority of acreage and now there's fan jets to reduce the water use.

Interviewer: Okay. As far as your site is concerned, do you keep track of pruning at all?

Sales Manager: I don't keep track of any of that, no.

Interviewer: Okay.

Sales Manager: The only thing that, and again I don't even deal with this, but someone in the field will deal with this. As far as on stone fruit, the amount of thinning that goes on, it's the amount of fruit that's left on the tree for the upcoming year. So they do it by hangers and by branches and so it's pretty detailed, but they would be better speaking about it than I would.

Interviewer: Would forecasting quality change the way that you'd be doing your things?

Sales Manager: For me, or for them in terms of this-

Interviewer: For you for making your forecast using greater understanding of quality?

Sales Manager: Yeah, that'd be helpful, because like I was kind of saying, that one of the biggest factors that would affect us would be rain during the summer on nectarines, so utilization is a big factor in terms of our forecast and [inaudible 00:04:15]. We have an idea of where they normally come in in it, but then sometimes they'll come in way below that for whatever reason. We don't always know what to attribute that to. For example, a normal peach pack out would maybe be like a 70, 75% utilization.

Sales Manager: Then all of a sudden we're getting like 50% utilization, and there's some sort of external factors that are affecting that, and it's usually pretty difficult for us to try and attribute to what it is. Another example is, no one's been able to attribute what... It's called staining or inking. If you Google it on peaches, you'll see it. When the fruit comes in, it looks fine, but then all of a sudden the stains up and then turns brown. Some people theorize that it has to do with hotter weather, will bring it on.

Sales Manager: There's also been theories that maybe the fruits dirtier, and some years are worse than others for staining, but no one's really found out what actually causes it. If you could somehow find out things like that or what those are attributed to, that would be pretty beneficial.

Interviewer: Would understanding the global economic environment and having forecasts about that help with your price setting at all?

Sales Manager: Yeah. I think it could help to a certain degree, but it's just like there's so many on some of these commodities as well that substitutes though. So yeah, that could definitely help, because if imported fruit was coming in at higher prices this year, then it would affect the amount of fruit that, you potentially in the South then you drive your prices higher. So yeah, that could be beneficial.

Interviewer: Would it be beneficial to know regional yield averages for the same type of varieties from your other competitors?

Sales Manager: Yeah. That would be helpful as well as information, if you had information on growing. California grows about 70% of the peaches, but then Georgia and South Carolina grow probably about 20, 25%. There's also a bunch of Northeast peaches and Colorado peaches and Utah peaches, and all these other little popup deals. So if you had some information, as far as those crops and whether or not they have a good yield or bad yield, that would definitely be beneficial.

Sales Manager: A couple of years ago, the South froze and impacted their peach crop, and so it drove California peach prices higher by 20, 25%.

Interviewer: As far as the yield and cost per block, and the cost of packing, is that something that would building a model about be helpful?

Sales Manager: Yes. That would be helpful, because that determines knowing your production, and the cost associated with it. It gives you a baseline of where you're trying to set your prices for, say your seven year costs or your contracts that break even plus whatever you want to make.

Interviewer: How happy are you with your current forecasting ability?

Sales Manager: It's pretty poor. It's pretty elementary, but it works, but there could definitely be improvements.

Interviewer: What would you like to forecast that you currently are not forecasting?

Sales Manager: What the heck? I'd say, ability to forecast the production is okay, but if there were things that could better forecast in terms of the quality or the sizing out in the field, those would be beneficial, because both of those are estimates that we use, but they're not always accurate. Then if there was also just a more automated way of doing it, because right now, we using historical information, putting it in Excel and then having them [inaudible 00:08:24] spit out. So it's still pretty user intensive.

Interviewer: What data would you like to have that you currently don't have?

Sales Manager: I feel like when you're talking about yield and neighbors yields and things like that, and growing region yields, I feel like that'd probably be one of the most useful things, if it was accurate. One other thing would be sizing and quality, so measuring the sizing that's out in the field, the size of the fruit. That's always a challenge for us to try and estimate, because some years it will be big, some years it'll be small, but if there was a way to more accurately do it before it actually arrives in the packing house, and we're running over the size, or if there's some accurate information from the field to us, before it's actually picked and packed. That'd be very helpful.

Interviewer: You mentioned also that rely heavily on expert opinion to make a lot of the estimates. What do you think could be done to make the expert opinion more accurate?

Sales Manager: I'd say it's just more user friendly data, because right now, you're having to pull information from a lot of different spots, and then you use all of that information, and kind of mush together to try and figure something out, and it's by no means a perfect science or anything. So if there was some way to get more information in a readily usable format, that would be ideal.

Interviewer: Okay, great.

Phase 3

Interviewer: Okay. So basically after talking with everyone for the last two phases, we came up with a potential predictive model with different areas that can be seen as impacting the yield and profitability.

Sales Manager: Okay.

Interviewer: So we're just going to go through each one of those and see if you think it's going to be valuable and how it could be accomplished. [crosstalk 00:00:30] So the first area that we're looking at is field forecast, which is really looking at the expert opinion of the yield quality of the fruit on that three week rolling scale. And then how it would change the current process is actually it would record the data as it went and as it got updated, so that the accuracy of the forecast can be compared via the actual data and then changes to the forecasting could be made. Is that [crosstalk 00:01:06] something that you think would be valuable?

Sales Manager: Yeah, that definitely would be valuable. The way it's done now is, it's more of a manual process. We'll do a weekly one where it's kind of what you're suggesting. Whereas the data comes in, it gets updated, but again, it's all done manually. But then the three week one, I do one shot of it and that's it. So what you're suggesting would definitely add value.

Interviewer: Okay. The next area we're looking at is the block level weather historical data. Whereas we'd be using weather service or localized sensors to track the weather over time at a block level, and then seeing how the weather impacts the profitability and yield.

Sales Manager: Yeah. One of the biggest factors associated with weather affecting the fruit would be like a move, like on Stanford especially it can move the fruit a day forward or a day back or a few days forward or few days back in terms of harvest and that's very useful information for [crosstalk 00:02:08] profitability and yield [crosstalk 00:02:10].

Interviewer: So being able to see kind of how different weather impacted it would then... If there was a dashboard created where you have a three week forecast of what is coming, do you think it would help change kind of how the field's managed through picking?

Sales Manager: Yeah. I don't think you'd be able to do it on the first year, but I think as you continue to get data and accumulate things and see how the weather actually does affect the three fruit in different blocks, would definitely be useful. I don't think anyone has that information readily available now. So I don't think there's anyone to say like, yeah, we look at it and things are going to adjust because I didn't get [inaudible 00:02:47] time [inaudible 00:02:47] no one does it. Yeah it may be useful if you guys can find a way to do it.

Interviewer: Yeah. Okay. The next module we're looking at is pruning and field management. So with that, we're looking at having a block level recording of what kind of pruning and very granular of density and everything about how the pruning is done. Because I know that it's currently being recorded, but it's mostly the financials of how much it costs is being recorded, but not necessarily what was done.

Sales Manager: Yeah. Yeah. Like you said, a lot of its just expert opinion and opinion and historical information based on the past. What they think works, and what they think doesn't work. But it's not as intricate as this would suggest.

Interviewer: Okay. And then the next area we're looking at is industry environment. We're talking about market supply. So if we have regional weather historicals from major competing, growing markets, like keeping track of what's going on in Georgia, Mexico, Florida. Would that have an impact of how the fields are managed or how things are packed or how things are sold?

Sales Manager: Yeah. Like an example, small changes in supply can have dramatic influence on prices. So for example, I think four or five years ago, South Carolina froze because they got cold weather. And so it froze the bloom on the peaches. And in terms of total peach supply in the United States, they only represent 10 to 15% of the total supply. But the pricing changes as a result of that 10 or 15% being out of the market, was maybe 25 to 30% price [inaudible 00:04:33] adjustment.

Interviewer: So would having a three or four week forecast of what their weather is going to be affect kind of how you'd be setting your pricing?

Sales Manager: Yeah. Yeah, it would.

Interviewer: Okay. The next area we're looking at is industry environment. In this one we're looking at market demand. So if we had economic indicators of consumer behavior, like unemployment, consumer confidence, spending on grocery items and historical sales and had a correlation model for all that, would that drive any of the differences in how you'd manage the packing?

Sales Manager: Yeah. Again, it would change the way you're pricing things, if you can anticipate higher demand and it'd probably change the packing but it'd definitely affect your pricing due to so much uncertainty as far as not knowing what a customer is going to take. And then if you have some sort of better information as far as how these different factors are affecting demand, that would affect your decisions for sure.

Sales Manager: And one thing that I think also to keep in mind, which I feel like it's kind of leading out to one of these subjects, but not, I don't know, necessarily hit the weather also like different areas. Which you'd never really think affects the demand that greatly, but an example is when a snow storm is about to hit, whatever, Indiana or Michigan during the winter, the demand just absolutely spikes right before the snow storm hits because everyone's going into the stores because they know they're going to have to huddle up for the next week. And so there's distribution centers that will just get completely wiped out. Probably not to the extreme of COVID, but it's a similar sort of situation where the demand can go up by 200% for a few days as a result of the weather and location.

Interviewer: How far of a forecast would have to be made in order to make it actionable? How many weeks do you think?

Sales Manager: A lot of the pricing done now is three to four weeks in advance. But even if you have like a week in advance, it would still be beneficial because on some of these commodities where the produce goes bad quickly, first stuff you don't have sold, you might take a lower price sale or just send it on consignment to the wholesaler. And basing it on consignment means basically you just give them the fruit and they'll give you whatever price back they want after they sell it. But if you know demand is coming seven days in advance or seven days out, then you'd probably just hold that fruit until you get those orders.

Interviewer: Okay. Okay. Out of all the areas, which area do you think is the most valuable to take action on first?

Sales Manager: I would probably say field forecast. Short term would be consumer economic environment, but I'd say longer term would be industry environment. When I say short term, [crosstalk 00:07:31].

Interviewer: So what was your number one?

Sales Manager: Field forecast.

Interviewer: Field forecasting?

Sales Manager: Yeah.

Interviewer: And then on a scale from one to seven with one being relatively difficult and seven being relatively easy, how difficult do you think it would be to implement something like that?

Sales Manager: I'd probably say three or four.

Interviewer: Oh, so you think it'd be relatively difficult?

Sales Manager: Like if we're trying to implement that I feel like it probably would be on the easier side of things. But I just feel like you need to have that industry knowledge to know exactly what you're looking at because I think numbers, especially in produce, can get skewed really easily.are you like had [inaudible 00:08:34]?

Yeah. I'd say probably somewhere in the middle. Whatever you said, from one to seven. [crosstalk]

Interviewer: Ok, so four?

Sales Manager: Yeah. Yeah.

Interviewer: Okay. Okay. Great. That completes everything.

Sales Manager: Cool.

Interviewer: Okay. Thank you very much. Bye.

Field Manager

Phase 1

Interviewer: What are your KPI (Key Performance Indicators) for your operations and what metrics help you define success?

Field Manager: The utmost priority is having quality control and the metrics of that would be personnel, along with constantly documenting and evaluating assessments in the field. Then, once it's reached the packing facility, we compare those matrixes against the packing house QC and the line determines what is packable for utilization.

Interviewer: How do you end up tracking those?

Field Manager: We track them through a log in a paper format. At the packing facility they would provide us a core report on those items. The aggregated data from the packing facility would be gathered in a way that allows us to compare yield data and production data.

Interviewer: Is the packout generated by the Famous software system?

Field Manager: Yes, it is.

Interviewer: If there are issues in the packout, are there drill down tools to look into the root cause of the issues?

Field Manager: There would be a discussion with the quality control manager regarding the loss or the degradation on the packout.

Interviewer: Do you have computerized dashboards or anything available to show data?

Field Manager: No, I do not.

Interviewer: Do you do any forecasting? If so, what kind of forecasts are made and are the forecasts checked after the season to determine their accuracy.

Field Manager: Yes, for example, we analyze the estimates for citrus, both from crop sizing standpoints and the overall yields. Then, we continue to gather and compare that information as we go through the year. We also have a clean pick schedule that's in excel format and we will compare our estimates versus the actual numbers.

Interviewer: What data do you use to make those forecasts?

Field Manager: It's more experience based, we go out and assess each block. We also use a caliber to provide size estimates, which assists in determining the subsequent size growth in an ideal climate or situation.

Interviewer: To confirm, you mainly use expert opinion for the forecasts?

Field Manager: Yes.

Interviewer: How do your operations change as a result of the forecast and the expert opinion? Do you take actions to try and make modifications?

Field Manager: Yes, if you are dealing with a light crop scenario, you may have to manage that in a different way than you would managing a heavy-set crop. For example, you may have to harvest earlier than you anticipated to keep the fruit from becoming oversized. We may manipulate cultural practices through irrigation deficit or fertility management to help us reduce the size structure if it's a light crop.

Interviewer: What aspects of your operations do you think more structured analytics would help you improve?

Field Manager: A field estimator and the ability to compare our inputs versus what we are doing in terms of production. The one thing that we currently do not have is the ability to aggregate yearly data and create dashboards that produce analytical trends. If we could create tables or dashboards that produce aggregated annual yield data to base our determinations off of, that would be an ideal scenario.

Interviewer: Looking into optimizing cost versus value, would labor and pruning consist of something you would track and modify as well, based on expert opinion?

Field Manager: Yes.

Interviewer: To confirm, you believe it would useful to track and modify in the same way? I know there is moderate forecasting conducted in terms of cost versus value, however, is it conducted in a way that is manageable?

Field Manager: It would be because we could track annual costs from a labor standpoint. Especially now considering that the cost of labor continues to rise, we are currently at thirteen dollars an hour which is going up to fifteen. Ultimately, if we were able to analyze that data year over year/block after block and then compare that to the yield output through aggregating the data altogether for evaluation purposes, that would be a great philosophy. It would also be beneficial to utilize the data pertaining to size matrixes. In doing so, it would eliminate our staff having to go back to run a report and examine the information year after year on a piece of paper.

Phase 2

Interviewer: Okay. Now to continue on from our conversation that we had a week ago, the point of this part is to look into how data is available, how better forecasts can be made and how experiments could help them. When we're looking into what information you think that your job would like to have forecasted, how does demand play into that? Is that something you would be interested in being able to understand more?

Field Manager: I would, I guess I'd have to probably noodle on exactly... So are you talking demand in terms of commodity demand?

Interviewer: Yes.

Field Manager: Or are you... Okay, so forecasting as it relates to commodity demand. That would probably come into play in our estimates, and being able to have viable estimates moving forward to give the marketing side a better gauge of what the crop load looks like. Is that kind of the processes that you were looking for?

Interviewer: Yeah. So you're saying that's the demand per... So having, being able to forecast the demand for commodity would help with your yield forecasts and...

Field Manager: Yes. Or vice versa. So let's say, hypothetically, we're running on a lower... Say we're on a off year, and we're able to see that ahead of time and kind of forecast that ahead of time and give the marketing team a heads up. And then they can kind of forecast their marketing strategies accordingly.

Interviewer: Would having historical access to weather data, as far as it has corresponds to the yield, the previous yields. Would that be something of interest?

Field Manager: Yes, it would. And the reason being is, because we can look at historical's, and similar degree days or temperature correspondence and see how that relates to, let's say 2012. If that was a similar year, we could see how that played into effect on our commodities.

Interviewer: Is the availability of water another area that you put into that same category?

Field Manager: Yes.

Interviewer: And then, you mentioned pruning.

Field Manager: Pruning. Yeah, pruning could play a part of it, or cultural practices, depending on your total crop estimates. So maybe we'd lessen our crop, or inputs in, in terms of pruning, or mechanical pruning and stuff like that as a result of a lighter crop. Or we enhance that, the cultural practice, if we know it's going to be a bumper crop.

Interviewer: When you're looking at your estimates, is there like a produce quality metrics that you're forecasting?

Field Manager: I've never seen one. I would imagine there's something out there. I think that would probably be a question for the sales manager.

Interviewer: Oh, okay. So when you're making your estimates of what you think is in the field, do you state what you have? Or are you making an estimate to the quality as well?

Field Manager: Its more what we have. And then in terms of quality would be like any cosmetics that we can actually see.

Interviewer: Okay.

Field Manager: And then we get a feel for what's going on industry wide and how... And comparisons for industry versus our internals.

Interviewer:

Okay. Would understanding anything about how other fields from other companies are going, help with your job at all?

Field Manager: Yes.

Interviewer: Would the global economic environment change the way that anything you'd be doing in the field?

Field Manager: It could, if commodity prices kind of continue to stay flat and then our costs continue to rise. I think we're going to have to assess where we're at, so that would definitely play into it.

Interviewer: And then, would the historical yield per block help in any way?

Field Manager: Yes.

Interviewer: Would keeping cash to your cost per block help as well?

Field Manager: Yes.

Interviewer: And then, is there currently a cost per packing? Is that currently done down per block or how does that currently keep kept track of?

Field Manager: Well, it's done by the carton and then we can backdoor that by figuring out the number of cartons to the acre, so that's feasible of accomplishing.

Interviewer: Except the things we've kind of talked about, is there anything else that, if there is a like giant equation that can be plugged in and forecasts could be made, is there anything that we didn't bring up?

Field Manager: No, because we kind of touched on the first interview about fertility side of things, and being able to track that and forecast that, based on a matrix or a logarithm of crop estimates.

Interviewer: Yeah.

Field Manager: And then you touched on water, which I think is going to start becoming more of a key player as we move forward and Sigma kicks in.

Interviewer: What's that?

Field Manager: A Sigma.

Interviewer: What is that?

Field Manager: That's a new law regulations that are going into effect in 2022, that we have to basically... We're going to be allocated so much water per acre foot, that pumping capacity's from the underground aquifers. And so we're going to have to manage and balance.

Basically, what we're trying to do is get a net zero as a basin, and we cannot have that basin drop, the water table drop, in the aquifer. So we got to balance pumping versus surface water and requirements for tree needs.

So for example, if we had a surface water of one acre foot and pumping capacities of one acre foot, but we need three acre feet, we're at a minus one acre foot capabilities of producing our commodity.

Interviewer: Okay. That makes sense. How happy are you with your current ability to forecast?

Field Manager: I think there's room for improvement.

Interviewer: So the main areas that you think that improvement can be made? [crosstalk 00:07:59] valuable things to the... What are those valuable points that, for your role, being able to estimate would... Not would.

Field Manager: I go way back to like citrus estimates and then also on tree fruit side, estimating crop yields there would be beneficial, then that would help us analyze our strategies for thinning purposes.

Interviewer: Okay. And what data would you like to have that you currently don't have available?

Field Manager: Paul's starting to slowly show me more of the cost center aspects of things, which I've never had access to. That gives us a real good tool to be able to compare our overall cost, so I think we're moving in the right direction there. Historical yields are available, but it's tedious to capture.

Interviewer: Okay.

Field Manager: And I mean, you kind of touched on stuff. I mean, I have access to like some of the historical weathers, stuff like that, so I'm just trying to brainstorm as I'm discussing here. I'm sure there'll be something that comes up as I hang up.

Interviewer: You did mention that a lot of your stuff relies on expert opinion. Do you think there's anything that could be done to make the expert opinion that you rely on more accurate?

Field Manager: Okay. So expert opinion...

Interviewer: So instead of being able to say, "It's basically historical domain knowledge." So knowledge from the workers.

Field Manager: So is there anything... I mean, I seem to-

Interviewer: Or is it just kind of a thing that exists and you rely on it, but you can't really put your finger on what it exactly is?

Field Manager: Yeah. There are situations that definitely that are that. And then there's also situations where you just kind of lean on your expertise in overall what you've seen historically, and you manage through it. So I guess there's a combination of both and it kind of probably depends on the practice that you were trying to do at that point, if that makes sense.

Interviewer: Yeah. Okay. Well, thanks very much. I'll get back to you next week.

Phase 3

Interviewer: Okay. So, in the phase three, from everything, all the feedback we got, we came up with a proposed predictive model of different factors that could be explored and recorded, that would build into a predictive model that could help with the profitability and yield forecasting.

Field Manager: Correct.

Interviewer: So [inaudible 00:00:26] and go through each one and ask a couple questions. So the first area that we were looking at was field forecasts. So that's primarily looking at the expert opinion and recording the expert opinion for yield and quality in a way where the forecast could be tracked over time. And then also the variance of the forecast from the actual results is also recorded. So that there'll be better traceability of how good the forecasting was and also how it can be improved in the future.

Field Manager: Correct.

Interviewer: Is that something you find valuable?

Field Manager: Yes, for sure. And there's also now new technology that actually will go in and I would think they're using some kind of... I don't know if it's got to be more enhanced in DVI or something, where they go in and actually image the field and they're able to do forecasting that way too. But we've never utilized that technology yet. It's still in its infancy stage.

Interviewer: Okay. So good. And then the next area that we were looking at is field weather. And when we're looking at that, it would be like a block level weather, historical data, as well as, that could either be weather service based or using sensors.

Field Manager: Correct.

Interviewer: And then that could create an understanding of how weather affects everything else. And then once that model is created, you can then have a dashboard that actually is looking at the three to four week forecast, to understand what's going on and how all that's going to be affected. Is that something you think would be valuable?

Field Manager: Yes.

Interviewer: Do you think that would be something that'd be difficult to do or is it-

Field Manager: [crosstalk 00:02:20] if it's at a field level, we would just have to have sensors available through the field and how that is communicated back to a central location would probably be the biggest logistical concern. [crosstalk 00:02:33] but I think it's achievable for sure.

Interviewer: The next area we're looking at is pruning and field management. And so in there we're looking at block-level recording of what was done and how it was done. Because currently I think it's all being tracked, but it's all being tracked basically just by invoices. And so it's not really the actual data of what happened, isn't really recorded in a way that is searchable.

Field Manager: That is correct.

Interviewer: And so that will be a value as well?

Field Manager: For sure, yeah. Because we could technically get down into our pruning strategies by block and have that on a dashboard or something and then be able to correlate that to yield or versus the weather and what transpired that could have actually had an effect on yield or quality.

Interviewer: And so the reason why that's currently not done is just because it's just not being recorded in the right way?

Field Manager: It is, but it's in a different area. So basically we would have to go back and then cross-check that against yield data, for example. Let's say hypothetically, we use pruning strategies, then we got to take the pruning strategy and then overlap that against the actual yield data.

Interviewer: Is the pruning strategy currently codified in a way that it can be compared? Or is it just kind of less descriptive?

Field Manager: It's less descriptive, but we could make it achievable where it is descriptive. And we could actually incorporate it somewhere where we can data track.

Interviewer: The next area, which I guess should be moved over in a sub of this area would be water availability and watering of the fields. Is that something you think would be valuable to track on a peripheral basis and being able to track over time?

Field Manager: Yes.

Interviewer: The next area is industry environment looking at market's point . So this would be like looking at regional weather from major competing growing markets. So it could be Mexico or Georgia or Florida, and building that into a rolling forecast, just like with the weather so that you can actually make actionable information based on the forecasted availability from other markets. Would that change what you were doing with your process as well, anymore, at all?

Field Manager: It could very well, yes. Because let's say hypothetically, Georgia, they have a small crop this year. So that's going to influence us how we probably go to market and market a little bit differently knowing that they're going to come up short or whatever the variable is.

Interviewer: The next area we're looking at is the industry environment and looking at the market demand. So that would be looking at economic indicators of consumer behavior. So that could include unemployment data, consumer confidence, spending on grocery items, and then historical sales, would having that information and looking at those indicators through the season change how you're managing the field?

Field Manager: To a degree they could. Usually by the time we get to that level, it depends on how early you would have that data available.

Interviewer: How much of a lead time would that data need to be available to be actionable?

Field Manager: To make it actionable, for example, we would have needed consumer data probably now to implement anything that we would do differently for the citrus, that will be starting harvest in November, December.

Interviewer: So about four or five months?

Field Manager: Yeah. I'd say six months, a lead time, to give you a little bit of a buffer there.

Interviewer: So based on the fact of knowing how the restaurants versus grocery stuff, are you guys changing how you're doing anything right now?

Field Manager: Not internally, but there is some changes being occurred in the industry as a result for lemons specifically. Lemons are in demand mainly from a restaurant or a garnish application. And so that is driving how growers look at the marketability this next year in light of the COVID situation with everything shut down.

Interviewer: Makes sense. So of all these areas, which one do you think is the most valuable?

Field Manager: The most valuable, I would say under the current regulations where the state of California is going, I think the water. Water would probably be in the most valuable.

Interviewer: To implement as far as building a predictive model to help into the future?

Field Manager: Yes.

Interviewer: To forecast profitability and yield?

Field Manager: Yes.

Interviewer: So tracking-

Field Manager: [crosstalk 00:08:12] did I throw you a curve ball there?

Interviewer: Yeah. Because from the last couple of phases, that wasn't something that was as brought up. Because we were expecting more of the pruning or field management or keeping track of-

Field Manager: [crosstalk 00:08:29] well, that would be probably my number two. I'm thinking now as we've gone through a couple of these phases, under the circumstances with water on the horizon, being an issue, I think that that's going to stand out and be a key critical component of profitability and yield moving forward, [crosstalk 00:08:56] followed by the pruning and field management.

Interviewer: So it would be like tracking watering cycles and how it's watered, how that affects yield?

Field Manager: Yes, that is correct.

Interviewer: And then on a scale from one to seven with one being the most difficult and seven being the easiest, how difficult do you anticipate implementing a system to record that?

Field Manager: I think that it's pretty achievable. I'm sorry, do the scale again.

Interviewer: Seven being the extremely easy and one being very difficult.

Field Manager: I would say it's going to be a four or five.

Interviewer: And do you think that once that's developed people would accept the results of that system and-

Field Manager: Yes.

Interviewer: ... take action on them?

Field Manager: Yes.

Interviewer: I think that's pretty much it. Thank you very much.

Field Manager: All right. Thank you,

IT Manager

Phase 1

Interviewer: What are your KPIs (Key Performance Indicators) for your operations and what metrics help you define success?

IT Manager: The KPIs would be revenue, net revenue, and gross sales. Our metrics consist of yearly changes in net revenue, which include sales minus the cost. We have our metrics well identified because of our ability to allocate costs down to different products that we are selling. Furthermore, year over year changes is a good metric but it is not always useful because the pricing of commodities changes so frequently.

Interviewer: Are you currently tracking what you determine to be your KPIs year over year?

IT Manager: We are but they must be taken with a grain of salt because there are a lot of variables outside of our control. We know over the course of many years which of those numbers we do have control over and the direction they are headed.

Interviewer: Do you have a system that generates reports and what kind of reports does it generate?

IT Manager: Yes, we have an ERP system that generates sales performance reports, as well as cost reports for accounting purposes. We have the ability to correlate those for the purpose of knowing what it costs in a given season to pack a commodity and we know what we are able to sell it for throughout the course of a season. It could also have a lot of variance, even within the same season. However, ultimately the answer is yes, we can track all those metrics within our primary system.

Interviewer: When you find issues that are flagged within the reports, do you have a drill down tool that allows you to find the root cause of the issue?

IT Manager: It depends on the report, some of the reports are dynamic and allow us to drill down. We also have a variety of different tools that interface with the same underlying data. Some of those tools do have drill down capabilities, while some are static reports. However, if you find a problem on a static report you can use that information to run a different report to track down the source of that problem.

Interviewer: Are there any dashboards available for high level information?

IT Manager: There are, we have a business intelligence system that summarizes information and can be scheduled to send it to certain individuals for performance tracking, daily auditing, and to display on monitors. Although, we have yet to utilize all functions since we have only had it for about a year.

Interviewer: Are the dashboards real time or do they have to be compiled?

IT Manager: No, they are in real time.

Interviewer: What kind of forecasts are made and are the forecasts checked afterwards to determine their accuracy?

IT Manager: I know we have harvest forecasts which are forecasts on how much of a commodity we intend to receive from a particular block or on a particular day, those are fairly accurate. A lot of it is based on the history of a particular field, along with factoring in conditions such as weather and other seasonal adjustments. In terms of the accuracy of that forecast, there are probably a good 5-15% variance in those but it is hard to count exactly until it is in your hands.

Interviewer: Are you tracking the accuracy of those forecasts?

IT Manager: We know there is going to be variance no matter what we do so we have to make sure the variance is acceptable and if the forecast is wildly off then there has to be a reason for that. Some of the reasons could consist of a failed crop due to damage or an insect. However, since we are using harvest numbers from prior years to feed into those forecasts, they are fairly accurate.

Interviewer: What data do you use to make those forecasts?

IT Manager: Prior year harvest from a particular block. We are not comparing field A to field B to conclude what field B is going to do this year. We are looking at prior years of that same field, which incorporates all the same variables that existed in prior years, excluding weather.

Interviewer: Do you rely on expert opinion to facilitate these forecasts?

IT Manager: I am not aware of us doing that. However, that doesn't mean that it doesn't happen, but I am not personally involved in it.

Interviewer: To confirm, you rely on data and not expert opinion?

IT Manager: Correct.

Interviewer: Have you changed your operations as a result of forecasts made or the data that has been collected?

IT Manager: I think when we anticipate that we are going to be bringing in a certain number of fruit bins, we need to decide on when it will be harvested and how big of a crew will be harvesting it. Ultimately, we need to make that determination as accurately as possible because we want to ensure that we are not overpaying for labor and we're doing it as efficiently as possible. We also want to ensure that we are not running out of labor or overloading their workload and running behind on orders. It is very important to keep the amount of fruit coming into the facility and the amount exiting the facility in somewhat a balance. We want to avoid the product on the floor from spoiling or not having enough product to ship out.

Interviewer: Are there any aspects of the operation that you think analytics could help improve?

IT Manager: We just started getting into some of the business intelligence/analysis side of things and we've used it to look at data in a different way. Potentially, growing our knowledge about some of the operations. It's complicated considering that it's already there and accessible but the people who would know what to do with it don't necessarily know what data is available. Ultimately, getting that information translated in a comprehensive format that pinpoints the useful data points for specific individuals would be of value. The data is there and we can access it, however, knowing what is important and ignoring the rest can be challenging.

Phase 2

Interviewer: Okay. Now, continue on where we were, based on session one, we compiled a list of possible forecasting and experiments, how experiments might help them. Of what you're currently looking at, is there any areas that you think that forecasting could be an advantage, like forecasting demand?

IT Manager: Clearly, forecasting demand would be advantageous because they would know roughly ahead of time what to pack and they could plan accordingly and pick to meet that demand. Right?

Interviewer: Right.

IT Manager: Of course, also, I was going to say forecasting harvest is equally as important because then you can-

Interviewer: So, yield?

IT Manager: Yeah, exactly. Then you can know what you're going to be packing and storing without overflowing or without running short of any particular product.

Interviewer: Are you guys currently doing any forecasting for weather?

IT Manager: SunWest, as a whole, probably is, but I'm not aware of it.

Interviewer: Then, is water availability forecasting something that's in the larger plans?

IT Manager: Again, I would assume that would be someone's job, but it's not related to mine.

Interviewer: What about keeping track of pruning?

IT Manager: Keeping track of what's been done to the trees?

Interviewer: Or different amounts of pruning or ...

IT Manager: Yeah, we do have a database that collects and stores data of all of the activity done to a particular field every year, so that we can use that data to go back and compare current workloads with prior years to get an idea of in three count or how long it took a crew to do a particular field, how much it cost us. That data is used and recycled to give us some forecast of the year to come.

Interviewer: Is that data looked at historically or not?

IT Manager: Yeah. We have year-over-year comparative reports that tell us kind of what we've done in the past on a particular block in order to gauge what we'll need to do this year. Of course, there's other variables in play, including weather and water and such, but it gives us at least a baseline.

Interviewer: Is the economic environment of the industry as a whole used for any forecasting?

IT Manager: I mean, the commodity prices, I don't know the impact that they have on demand. I'm not real sure, tell you the truth.

Interviewer: Okay.

IT Manager: Well, it wasn't just commodity price. It used to be industry in a whole. I do know if other parts of the country have severe weather or other impact on their crop quality or yield, that we can tell that that's going to have a rippling effect on that commodity price in general, but it is usually delayed. It will take a week or two for the impact to be felt, but if, for example, there's a hurricane in the Florida orange crop or the Georgia peach crop is damaged, of course, that does have a pretty big impact on our commodity prices.

Interviewer: Is that type of data, though, taken into consideration on the system, or is that more of an expert opinion kind of thing?

IT Manager: It's more of an expert opinion, and we'll see the effects of that in looking at the market and seeing commodity prices as they get adjusted as the market reacts to those things, but we can predict some change based on those occurrences, but it's not tracked in any system currently that I know of.

Interviewer: How happy are you with the current ability to forecast?

IT Manager: Generally, I think the places where we're doing that and using a system to do it, I think it works fairly well, but as we pointed out, we're not capturing every piece of data that we could. Some of those things are kind of expert opinion only, or we're getting the after effect of those changes, more reactive than proactive.

Interviewer:

What would be an area that you'd like to forecast that you currently are not forecasting?

IT Manager: I'm trying to think. I think where we're doing it, we're doing a pretty good job, again, especially looking at work that's been done, costs that have been incurred historically. They all kind of create patterns that we can at least follow and gauge what's happening. I can't think of anything that we can track that we're not currently that would be helpful.

Interviewer: Is there any data that you'd like to have that you currently don't have?

IT Manager: Not personally for myself, no.

Interviewer: Okay. Of the expert opinion that is relied on, is there anything that you think could make that more accurate?

IT Manager: I would think that you wouldn't want to rely on just one expert opinion, but rather a consensus of experts, an average opinion across whatever that question may be. I'm sure there's publications and some analysis that's bigger than just one territory or region or company that are done industry publication-wise, but I would hope that we're not just relying on any single person's opinion for any of those things.

Interviewer: Okay. Sounds great.

Phase 3

Interviewer: Okay. After talking with [inaudible 00:00:07] that if it could be put together, we're trying to find the usefulness of each of the factors for our predictive model.

IT Manager: Okay.

Interviewer: The first module that we'll be looking at is field forecasts. In that, we're talking about expert opinion of what the yield and quality of a field is, and how they do a rolling forecast, and trying to keep up with what they have in the field at any one time for their planning. If this was recorded in a better way to track how accurate the forecasts are over time, and keeping track of the accuracy, would that be something that could be helpful?

IT Manager: I think so, because it would increase the reliability of that information in the future when you need to rely on the forecast again. Right?

Interviewer: Hold on one sec. I'm going to [inaudible 00:01:05].

IT Manager: Mm-hmm (affirmative).

Interviewer: Okay. You still there?

IT Manager: I am.

Interviewer: Okay. Can you repeat that? Sorry.

IT Manager: I was saying that I would think that using that information and tracking its accuracy better would help, especially if that information is in a positive feedback. Right? So that you can trust the information more moving forward, if you determine its accuracy in the past.

Interviewer: Okay. So, that would be helpful. Now, next we're going to be looking at field weather and with that, we're talking about global weather history data, which could either be done via localized data from the National Weather Service or inter-narrative [inaudible 00:02:07] sensors into a new plugin system that could actually track the weather per field over time.

IT Manager: Okay.

Interviewer: And then could be used looking year to year. Is that something that you think would be valuable?

IT Manager: I can't imagine that the sensor level data would be all that valuable, or I should say I can't imagine that it would be more valuable than weather service data, just because weather isn't that localized. You're going to have a weather system that's going to affect everything in a geography. Right? Your fields that are in close proximity, you're probably going to experience very similar effects. I would think that doing it at the high level would be good enough. Now we're talking weather history, not weather prediction, right?

Interviewer: Correct. Weather history, so that a correlation between field forecasting, and yield, and then what the actual is over time. Because the entire idea of this model is to look at all these different factors in either the past, or the future, or real time. And be able to either increase the reliability of the model of the forecasting for the next year and the planning, or to be able to create a realtime dashboard that can say, "Hey, this is going on right now, which means this is how it's going to affect the yield in this way."

IT Manager: Right. Yeah. I think tracking it would be helpful, because then you could make the correlation between yield quality, whatever. Yeah. Tracking at a high level is probably sufficient.

Interviewer: Okay. So not even the yield, just the general areas should be better.

IT Manager: Probably.

Interviewer: Instead of fields. Okay. The next area is pruning and field management. Would keeping track in... Because I know at some level it's being tracked in the ERP system, but it's not in a way that's currently usable of keeping track of every single thing that happens in the field. So, we're talking fertilizer levels, pruning, everything that has to do with the field.

IT Manager: Yep. Application of different chemicals, irrigation models may be right, all those different [crosstalk 00:04:17].

Interviewer: Yeah. So the next model after this, we were going to talk about just water alone.

IT Manager: Got it. Okay. So, in field management [crosstalk 00:04:22].

Interviewer: Actually, so you're saying water should actually be included? Those two you think should be included together?

IT Manager: I think so. It is work that's done to a field. Right? And that stuff, it may be tracked independently. I agree that keeping a history of it in a way that is easily accessible and can be related to other data points would be helpful. And you're right, we do have a history in the ERP system, but mostly in terms of work that was done in labor and the cost associated with it, the bill associated with that labor, especially if it was contracted labor that did [crosstalk 00:05:03].

Interviewer: But, not precisely what was done?

IT Manager: Exactly. We do have access the information that this work was done to this ranch, on this date, by these people, but it's not [crosstalk 00:05:15].

Interviewer: It's not [crosstalk 00:05:17] in a way that you could tell exactly what happened, right?

IT Manager: Yeah. You can't ask the system, "Show me everything that's happened to this piece of land." Right? Because it's all done based on the billing aspect of it, not really the land management aspect of it.

Interviewer: Okay. So, the next module, we talked about water so that we're going to lump that in with those two together. Then, next one we're looking at is industry environment, which in that we're talking about regional weather data from competing growing markets, or even things that are going on across the country with others with the supply of competing products.

IT Manager: Sure. That affects the commodity market as a whole. If you have other weather systems and other geographies, I know there have been cases where entire crops have been lost because of hail, or bugs, or what have you. Right? Yeah. That affects the market. So I guess the question is, do you track that data and correlate it, build it into your model? Those things are generally pretty hard to predict and they're random, right?

Interviewer: We could be having a data point that says... Or, the hurricane forecast for Georgia, for example.

IT Manager: Sure. Maybe base it [crosstalk 00:06:42].

Interviewer: And if there is hurricane coming in, then you know that the supply chain for the fresh produce in Georgia is going to be affected. And so therefore the demand in California is going to be going to be increased.

IT Manager: Increase. Yep. And you can assume that lower supply, higher demand is going to lead to higher prices. Right? And especially, I guess if you are tracking that over time, you can see, not just annual, but greater weather patterns, like El Nino cycles and stuff like that.

Interviewer: If there was a real time dashboard that had a three week horizon on it, do you think that would be valuable for sales, for example?

IT Manager: That kind of stuff, like I said, it happens so infrequently and it's so large. I wouldn't think that you would get much value out of that narrow of a view. I think it would perhaps feed into a forecast model on an annual basis on predicting.

Interviewer: Just to explain variances?

IT Manager: Yeah.

Interviewer: Okay. And then the next model we've got is consumer economic environment, where it's looking at the demand side. Where it could be economic indicators of a consumer behavior at unemployment, consumer confidence, spending on grocery items and historical sales to look at the correlation between all those things and to understand when something's happening in the economy, how that's going to affect demand, and how you might choose to pick or not pick different quantities based on that.

IT Manager: Yeah. It affects demand and pricing obviously. I think the COVID epidemic is a great indicator of that type of thing. Right? Where restaurant demand has changed quite a bit, so we might not be selling as much of our product to restaurants because people aren't eating out very much, but people are still eating the same amount of stuff. They're cooking more at home. So, where we have lower demand in some commodities, we might have higher demand in others to meet that. That's definitely information that would be helpful in forecasting demand. And of course, demand feeds into potential market pricing as well.

Interviewer: Okay. I think that covers it all. What do you think is the most valuable out of all these modules that you think?

IT Manager: Honestly, I think probably the weather and the field management give you the most granular information. Everything else is, we talked about markets and big weather and disasters and stuff, it's very slow moving. But, I think your yields, which gives you and it's something that you can control. You can't control all these other market indicators, but you can certainly control what you're doing with your own product. I think the best and most valuable information is going to come from internal in terms of how we spend our money, the practices that we're doing our land, and you could even pull yield data from that and see where we're doing something different. If it's having a beneficial result, let's do that different thing in other places.

Interviewer: And then on a scale from one to seven, with one being a very difficult and seven being very easy, how difficult do you see implementing a system like that with all the metrics we've been talking about?

IT Manager: Again, the ones that we have control of and access to currently, because they're products and practices that we're doing-

Interviewer: No. I mean within the field management.

IT Manager: Okay. I would say five. I would say it would be relatively easy. Because again, the data, it's there, it's just a matter of packaging it in a consumable manner.

Interviewer: Okay. And then how do you think people would accept it? Do you think they'd go through the extra processes? Or do you think that's going to be an issue?

IT Manager: I think it would be an issue short term, just because in general, people are somewhat skeptical and resistant to change. But I think once value is shown, and of course you'd have to go through a couple of season cycles to get to that point, right? But, I think once value is shown and as long as the data is easy to work with and easy to access for the consumer of the data, and that might be different people doing different things with that data, I think it would be easy for them to get behind once they see it makes their job better or the product overall better.

Interviewer: Okay. That's it then.

IT Manager: Very good.

Interviewer: Okay. Thank you very much.

IT Manager: Not a problem. Bye.

Controller:

Phase 1

Interviewer: What are your KPIs (Key Performance Indicators) for your operations and what metrics help you define success?

Controller: The KPIs on the farm are always yield, cost, and then price factors in afterwards. In terms of packing, the KPIs are productivity of quantity. The other metrics are concerned with labor in the packing house.

Interviewer: To confirm, your stating that operations are in three different sets. The field is concerned with yield, packing house metric is productivity, and sales which is based on price?

Controller: Yes.

Interviewer: Of those KPIs, how do you track the performance of those?

Controller: The yield are tracked by actual activity through a recording program that we have for reporting all activity coming out of the filed. Then, you have the receiving and the pack-outs which are in the plant. Once the product arrives in bulk there is a pack-out which is done as they are packing the product out. From there, we will compare that to the actual acres to get the productivity or the yields. Productivity in the plant is generated by how many boxes they put through and how much labor was necessary. Sales is more difficult to assess. About two thirds of our sales is on contract pricing and the rest is on market pricing. Contract pricing is determined for the season and the market pricing is determined by whatever the day may bring.

Interviewer: Could you elaborate on the contract pricing?

Controller: For our major vendors, we went out and generated contracts based on a certain quantity for the year. It doesn't state the specific size, but it is based on quantity and a base price for that quantity. If the packaging changes from the base, there will be an upcharge. However, the standard box has a set price that is determined for the season.

Interviewer: To confirm, you have pre-set pricing before the season starts?

Controller: Yes.

Interviewer: On the reports, what kind of reports do you generate?

Controller: For the yield, I generate a pack-out report which will show what was packed out on a weekly basis. These reports show how many boxes were packed and how many bins were used to get those boxes. It's done by grower and by block, so we know exactly which block is producing how much. Within the plant itself, I only generate reports on a seasonal basis, not on a daily or weekly basis. Getting information on any individual block within a short period doesn't mean anything. This is caused by numerous issues that might arise like as re-packs and returns that would inhibit the whole quantity completion of the block. Then, if it is sold and comes back, this could also change the quantities. For sales, the same weekly report I conduct for pack-out will show the average quantity and average price on an equivalent basis for whatever they sold for the week, year to date.

Interviewer: If you find issues within the reports, do you have tools in place to conduct drill downs to find the root cause of the issues?

Controller: Yes, any inquiry report in Famous can drill down and go back to see where the initial input came from. For example, if you have an invoice you can drill down to determine what that consists of and what the adjust is. For pack-out reports, you can figure out when it came in, what bin it came in on, and the day it came in. Ultimately, it can drill down on all specific information.

Interviewer: Are there dashboards available? If so, what kind of data do they show?

Controller: Dashboards are available, but I don't use them because they don't provide useful information for the kind of reporting that I conduct.

Interviewer: Moving into forecasting, what kinds of forecasts are made and are the forecasts checked for their accuracy every season?

Controller: For citrus and mandarins, there is a report that is generated at the beginning of the season and it contains the projected number of bins. All the forecasting is conducted by bins, not cartons. There is a report that projects how much we are expecting for the season and it's updated on a weekly basis until the season is over. However, we don't have any reports that are as specific for tree foods, other than a rough estimate that comes from the field manager. The field manager usually only determines whether it is going to be more or less than the previous year. Obviously, there are no projections for the packing house because they will produce whatever comes in that day. That is planned on a day-by-day basis, they have a weekly schedule on what they plan to do but it changes constantly.

Interviewer: What data is used to make those forecasts?

Controller: The forecasts is based on two things, sales requirements and what the field managers determine the quantity is that is ready to be packed. Citrus is a little more flexible because it will hold longer.

Interviewer: Regarding your seasonal forecasts you discussed for citrus, what kind of data was used to generate those forecasts?

Controller: Again, it's determined by the field managers and the foremen that go in and examine the tree, the buds, and the size. From there, they will an estimate on each block for what they believe that field will generate.

Interviewer: To confirm, it is primarily expert opinion?

Controller: Yes, they do not have anything that will make projections because it changes drastically based on a multitude of variables.

Interviewer: Have you changes your operations or taken any actions based on the results that the forecasts made?

Controller: From the forecasts, there is really nothing we can change. The forecasts are for the citrus that is updated weekly, but it doesn't affect anything. We don't have a real projection for the cost of the season, we just have a projection of the estimates that they update. However, these estimates don't change anything, it just remains a number until the season is over.

Interviewer: What aspects of the operations do you think analytics could help improve?

Controller: A big area would be the field cost; the analytics could help show what we've done in the past and if it's valid or not. For example, there's a great debate regarding how much pruning and how much thinning needs to be done on a particular variety. The question is, does additional pruning (that might provide bigger fruit) cost warranted? Are you spending more money to get bigger fruit than you would get if you had less pruning, generating smaller fruit and would that equate to more volume and more sales? Ultimately, analytics could tell us if some of the field work we're doing is really benefitting us within the big picture. In the packing house, analytics could tell us if we are being efficient in our flavor versus quantity. Currently, the way that they determine how many people they need is based on an estimate. If you could put together a better estimate or fine toon what's going to be coming into the plant, you could determine the head count more efficiently than we are doing now. Sometimes we have employees come in and there's no work to do because the food didn't come in.

Phase 2:

Interviewer: Okay. So continuing from where we left off, the next section is about, we're trying to figure out what data we have, and what data you think better forecasts and experiments could be designed around. So what would you like to forecast ... So that we have a bunch of suggestions here, to what extent are you forecasting demand? And to what extent would you like to forecast demand?

Controller: Okay. Now we're talking for packing it, so we're talking about the field? Or are we talking about both?

Interviewer: Both.

Controller: Both. Okay. Well, the problem with the field, as I know it is. You could forecast somewhat with citrus, because it could stay. Tree fruits, the forecasting is a little less accurate because it's picked when it's ready. So forecasting for that is sort of short term, which is good too, but even forecaster in the short term, it can help to schedule packing within the facility. So one leads into the other, where if you just wait until it's picked, or the day before, we end up obviously with having the wrong staffing for what's coming in. So we publish something like a weekly forecast, or projection of what will be picked in the following week would be helpful for scheduling purposes.

Interviewer: What about yield?

Controller: We do yield a couple of different ways. We do it on bin and we do it on carton. When they pick it in the field, they're doing it on bins. Now, when they're picking it in the bins, they're not being overly selective. So you'll have multiple sizes, you'll have [inaudible 00:02:04] included in the good fruit. So you can anticipate bins, but that's not necessarily how it would relate to actual cartons. You could do it based on history and say, "Well, okay, we usually get 75% pack out." And you could project from that. But sometimes projecting, is almost on a tree by tree basis, depending on how the fruit grew. It's a little more complicated, and projecting it again, you have to use parameters based on history. And yeah, it's not a bad idea. If you use parameters based on history, come up with what kind of numbers you usually get from each variety or each tree could help project how much good food would actually come into the packing house.

Interviewer: What about weather?

Controller: Well the weather just affects the yield, and it affects the crop. That would be part of the projection. The impact from weather is known before you get to the harvest, depending on the type of weather it is. If it's something as extreme as hail, obviously you already know the damage done. If it's too much sun and not enough water, sometimes you'll have a different quality of fruit. Size of the fruit is created to a large degree through thinning and pruning. So some of that is controllable to a degree to try and create the larger or smaller fruit. And even then if based on history, and based on doing the same practices continuously, you could come up with parameters of what we should get, all things being equal, from any given block or tree.

Interviewer: Do you think knowing more information about the external economic environment would help?

Controller: Such as what?

Interviewer: External prices in other regions, other competition.

Controller: Pricing will have nothing to ... The only time pricing has a issue, that would have to go back to when they do thinning, which is too far ahead of the game. Thinning helps create a different size fruit. If the pricing structure is based on larger versus smaller fruits, and you want larger fruit, you're going to have less fruit on a tree, but you'll have larger fruit. So if you want to anticipate a higher price for larger fruit, which isn't always accurate. We have customers, I think that some of the customers like smaller fruit rather than larger fruit. But if you try to control the size of the fruit, because you get a different price, then that would be the way to do it.

Interviewer: So from our last conversation, you mentioned a lot of what you're doing on your reporting is when you get to the end, you're figuring out what the actual yield, and the costs, and the packing per block all was.

Controller: Yes.

Interviewer: Would being able to forecast that going into the season, be of value?

Controller: The only person that would be a value to would be to possibly myself, and believe it or not possibly your father. Just having an idea or a anticipation of a projection would only be for projecting a financial picture. Doing that, it ... I mean, if you look at the reports and I have too many times, year by year the same block could change drastically. So to project it, then that's going to react in the field to a projection that says, last year you got 500 cartons to the acre. This year we're only going to get 250, or double it. So they react almost on a day to day basis of going out there and taking a look and saying, "Okay, this one's ready. Let's pick this today." The projection or the estimate of what might be, they won't react to it. They won't have the right staffing time to deal with it, because it could be way off based on history.

Interviewer: Overall. How happy are you with your ability to forecast? Satisfied or not satisfied?

Controller: Forecast financially, or forecast quantities? If you're talking about forecast financially, based on parameters, I could do a pretty good job of forecasting financially where we're going to be, and what's going to happen. Forecast as far as quantities go, I've been watching this thing for years and the volumes change so drastically so quickly. I mean, you could have a block one year that's doing great, and the next year, all of a sudden, and for sometimes unknown reasons, there's nothing. So forecasting quantities from everything that I've worked with just doesn't seem to be very accurate, would be just a hit and miss game.

Interviewer: What kind of data would you like to have that you currently don't have access to?

Controller: What kind of data?

Interviewer: Yeah.

Controller: That I don't have access to? Quite honestly, we've got access to almost everything that I need. Got access to all the cost information based on the programs we put together. Pricing is, as I mentioned last time, some of it is contract, which we have. The rest of it is market, and that'll change day to day. We have most of the information, or I have most of the information that I need to do any kind of forecast, or project for final numbers. I'm really not at a loss for having information.

Interviewer: Okay. What do you think could be done to make ... So for any of your jobs, do you require expert opinion to build your results?

Controller: Expert opinion to build my results.

Interviewer: The only reason that ... Instead of being able to focus on data, you're relying on just it's the way it's been done.

Controller: No, I never do that.

Interviewer: Okay.

Controller: But we'll change things if possible. But expert advice ... In the past couple of years, I'm sure you know we've had couple of outside companies doing reviews about work for various reasons. Even when they were looking at what we have, they had very little questions or suggestions on anything outside of the way we're doing it. I'm sure somebody could come in and tell me how to do things easier or better. I'll never be that egotistical. But it fits what we're doing, and it gives us the information that we want, the way we have it structured now. If somebody could come up with a better idea, by all means, I'll listen.

Interviewer: Okay. Okay. Thanks very much.

Controller: That it?

Interviewer: ... sectors.

Controller: It's a manual tag that they would fill in for each block, and each contractor, and each category or phase that they do. We just finished automating it. We'd put tablets out in the field. Except for only one. so then instead of manual tag they'd have to go into somewhat the first entry of the system. We've now got it automated where we put it out in the field and it just gets downloaded. We eliminated time. We've got better accuracy. So yeah, anything that somebody comes up with, we'll try.

Interviewer: Okay.

Controller: All right?

Phase 3

Interviewer: Okay, are you there?

Controller: I'm here.

Interviewer: Okay. We're looking at that proposed predictive model, and the areas that we're going to be looking at is asking questions about how each one would work.

Controller: Yes.

Interviewer: We're looking at our field forecasting module that would be looking at more of the extra opinion of their evaluation of fields. If that data would be recorded and the reliability of the forecasting could be recorded.

Controller: Yes.

Interviewer: Do you think that would provide value?

Controller: It would provide value to say where they start with and where we end up with, and what the criteria is they use to see how accurate their projections are and why. If all things being equal, this should be a basis that they work from, not just to guesswork.

So, I think it would be helpful to give a trend of how they're determining what they expect us to yield. So, yes.

Interviewer: Okay. The next module we're looking at is the field weather. If we had the ability to get information from the weather service and/or localized sensors to correlate down the block level, do you think that would be valuable?

Controller: The weather information would have some value, but everything on the field is more longterm than current. So, having current information, it would have to be exactly, and weather it just isn't the same from period to period. It would just give us some information that could give us a trend of how things yield based on types of weather patterns, but that's not all inclusive. So, I think it would have some benefit, but I'm not sure how much.

Interviewer: Okay. The next module we're looking at is pruning and field management.

Controller: Yes.

Interviewer: Would keeping track of what is done to every single field, and having a way of codifying it so that it's more descriptive, would that provide a value? I know it's currently done via cost, but you can't really do any planning off of that.

Controller: Well, actually we do have the information of what they ... We have all the details of what they prune by tree. But yes, if we have a lot of good information, because we're constantly trying to determine-

Interviewer: Can you currently report on that information, across different trees?

Controller: Yes. When we give information on the field of pruning, they tell us how many trees they pruned and how much time it took. So, we're paying them for the tree work.

Interviewer: When it's recorded in the database though, is it recorded by how much was pruned and what type of pruning was done?

Controller: Type? Well, when you say type, the only-

Interviewer: Like how heavy of pruning was done?

Controller: No, that we don't have. We just have two types, which is just regular pruning and summer pruning, and that's just a timing thing. But the number of trees that they do and the time it takes, we have that. And what [inaudible 00:03:16] we have. And it's relevant, because pruning has a direct impact on what the size and the quantity of fruit you get. So, it helps to determine the size that we're getting versus the price that we're getting, is the pruning actually giving us more or less pruning, generating a better price, than if we didn't prune and got different sizes. It has a direct relevance to what we are selling. So yes, that would have a lot of good information.

Interviewer: Okay. The next area that we're looking at, as part of that, is water availability and how much water was given to the field as well.

Controller: Well, watering is tough because water they just do as needed. Depends on weather. Depends on dryness. Depends on rain. From everything I know on water, it's really just as needed. They water as needed.

Interviewer: Okay.

Controller: They know the water. Today could be different than tomorrow. If it rains, because it's going to change.

Interviewer: Okay. So the next area we're looking at is industry environment. And with that, we're talking about regional weather data from major competing growing markets. So, it could be Mexico, Georgia, Florida. Would keeping track of that, and being able to build a model about that, and then looking at the forecasting on three weeks, have a better understanding of the industry supply be valuable?

Controller: Okay, wait. Industry environment. You're talking about the weather?

Interviewer: Yeah. Different things that affect the supply in the rest of the industry. One of the things that we've heard about was, like there's a hurricane going to Georgia, that will affect the market supply, which will then affect the pricing to replace those goods that don't end up being shipped.

Controller: But now you're going through timing thing. It depends on when that weather hits, and when they get their-

Interviewer: It would be tracked on a rolling basis, so there would be a time component.

Controller: The only time we can react to somebody else's weather issues is if it's extreme, and we know that something's going to happen. If it's just a small impact, we won't know that there's anything until ... We couldn't react to that. We could only react to a major catastrophe and-

Interviewer: Well, I mean by tracking the weather service data of those areas, if you know three weeks out that a hurricane is on the way, would that change how you're shipping and how you're packing?

Controller: You know, it can't. The fruit has to be picked when it's picked, when it's ready. You can't pick it early because there's a hurricane coming, because it wouldn't be ripe enough? It wouldn't be ready.

Interviewer: Okay. Okay. Then the next one we're looking at, the industry environment and looking at market demand. With that, we're looking at the economic indicators of consumer behavior. It could be unemployment, consumer confidence, spending on grocery items, historical sales, and building a model about all that to understand how different economic indicators could affect demand. So again, we would be creating an end of season model looking at the overall, and how the factors correlated over time. And then, being able to have a dashboard to say, what's going on in the world and how much should be packed, versus how much should be not packed because there's a substantial cost of the picking and packing portion.

Controller: I don't know. The problem with fruit is that it's a permanent planting. You're not going to change anything from economic indicators. The only thing you might change a little might be size. But you really can't change anything. It's locked in what you're going to have. You have to be changing your planting structure, which takes years. The only thing not indicated it would affect would be price.

Interviewer: Okay.

Controller: If you know that there's going to be a shortage somewhere else, you could probably increase your price, but you can't change anything to do with the production.

Interviewer: Okay. And then after looking at all these different modules, which one do you think is the most valuable to actually act on?

Controller: The most valuable to act on, there's two of them. I think pruning is exceptionally valuable, because then you're creating the type of the size and the volume. So pruning is very valuable, and field forecast is just a projection. I think pruning is about the only one that you try and control what you're actually going to grow and pack.

Interviewer: With a scale of one to seven, with one being very difficult and seven being very easy, how difficult do you think it would be to implement it?

Controller: The pruning? We already have that. To implement, that would be relatively easy because we have the data, and we're recording the information. We're already doing that, so that would be the easiest one.

Interviewer: And you think it'd be fairly accepted by the workers?

Controller: The workers, it's not going to matter to the workers. We tell them what we want.

Interviewer: Okay. Yeah-

Controller: As I said, we're already-

Interviewer: Because we keep changing the format in which they're reporting the data so that it can be recorded more gradually.

Controller: They're already reporting it.

Interviewer: Okay.

Controller: That's what I'm saying. That's easy. We're already reporting it.

Interviewer: It's just a matter of codifying a different in the database?

Controller: That's right. Yes.

Interviewer: Okay. Okay. Then that's about it then.

Controller: Okay.

Interviewer: Okay. Thanks very much.

Controller: Sure. Bye.

General Manager

Phase 1

Interviewer: What are your KPIs (Key Performance Indicators) for your operations and what metrics help you define success?

General Manager: The KPIs are built around the costing model, it's all driven by year input costs, primarily materials and labor. The one part that we have managed to control more than anything else would be daily labor costs. We run that KPI by labor costs per bin, 900-1000 pounds of harvested product and we recently included that on a per carton basis to see what our management effectiveness is for staffing. Ultimately, making sure that we are not bringing in too many people when we don't have a need for carton packing. A lot of what we do is pre-sort by size and grade, then it's final pack goes into bags. We pack to order from pre-sorted fruit. Our KPIs consist of that and the materials involved against what our packing charges would be. That provides us with the base components of what we are doing, as far as our costs.

Interviewer: How do you track the performance of that? I know you have a couple of different systems.

General Manager: We do but most of the information is taken from either our time clock system or our production system, which is Famous and that is moved into an excel spreadsheet. We've established target ranges that we try to stay within identify how we are performing within a range and if are outside of the range. Most of the time, if we find ourselves outside of the range it's below and caused by through-put production that we don't have scheduled. Some examples are mechanical, staffing, or quality of fruit.

Interviewer: When it comes to reporting, what kind of reports do you generate?

General Manager: Basic excel spreadsheets, which produce graphs, charts, and number that show what our target expectation is and how we're performing against that target. We'll also take the daily time sheets and identify whether anyone is working outside of their scheduled shift times. Then, following up to understand what may have caused extra time for an employee, sometimes special mechanics have down time repairs they need to take care of and adjusting for those things. Sometimes the events that occur during the day are unscheduled and we must adjust for those within a production system.

Interviewer: To confirm, you have the production system but in order to get translate the data into a meaningful way for reporting, you must transpose it into excel spreadsheets?

General Manager: Exactly, the Famous system is an oracle database and it will generate reports that you can save into excel spreadsheets. Although, it takes some time and manipulation using the information within the spreadsheet to get it into a user-friendly, functional level. Then, we run our calculations and our KPIs to make it all work.

Interviewer: Within the excel spreadsheets, are there drill down tools available in case you find issues that get flagged within the reports?

General Manager: No, it's all taken by management and the key managers. Once we dissimilate that information and identify where we might have corrections that are necessary. We simply move forward with making necessary corrections. There is no formal process or format that's used beyond the initial report.

Interviewer: Once you generate the report, is there a way of going into the block levels and determining the individual cost that could be contributing to the outliers?

General Manager: If we are talking about block levels, that refers to farm production and I have not seen any reporting from here that gives us feedback from the farm to identify where the quality of the raw product size, grade, or color (that determines harvest timing) affects the KPIs here. Other than the quality assurance check on the front end, however, there's no correlation between the quality there and the costs here.

Interviewer: Are there dashboards available, to examine that at a higher level?

General Manager: No, we have no individual one-off spreadsheets.

Interviewer: To confirm, that information is not in real time?

General Manager: No.

Interviewer: What kind of forecasts are made and are the forecasts checked to their accuracy?

General Manager: Forecasts are made, there is a rolling three-week harvest estimate that is produced by commodity and size. The accuracy of those forecasts is not validated, we use it as a guide for planning. The sales team uses them to plan for sales, we use it to plan our material needs against what the sales will have. Ultimately, the forecasts are a rough guideline and then it's reactive after that. It's not anything that I feel is accurate enough to build costing models against because of the changes from the quality of the product coming in and the reality of sales produced. For example, if the sales team is expecting medium sized fruit and we receive small sized fruit, they must react by adjusting their sales strategy with the individual customers that they have. We're also reacting to adjust our pack plan with materials as well. Ultimately, there's a large inefficiency by not having accuracy dialed in.

Interviewer: When making those forecasts, do you rely primarily on data or expert opinion?

General Manager: It's a combination of both, but it's conditioned by experience. Call it expert opinion but we take a look at it by observing what we have to work with and create a plan. That plan is developed from the personnel here with many years of experience, all the way through from sales to production. They determine what we have to work with and how it will be processed, changes are made on the fly.

Interviewer: Are there a lot of actions being taken as a result of those forecasts?

General Manager: Yes, constant changes throughout the day.

Interviewer: What aspects of your operations do you think analytics could help improve?

General Manager: I believe taking the information from our forecasts and evaluating it against our results, thus refining the accuracy of that information would be a plus from analytics. A lot of that is driven by the value to the field operations and they would find value in their costing models for harvest and return-to-farm in case they are off on their estimates by a size definition. Analytics could navigate impact on smaller pieces of fruit since it takes more to pick that off a tree, as oppose to medium or large fruit. Ultimately, getting all of that dialed in would have great value and something that I’ve tried to do by myself over the years, but it continues to be on an as-needed basis. A dashboard real-time model would be helpful.

Phase 2

Interviewer: Hey. Okay. So now to pick up where we left off, this next section is going to be looking into forecasting and data and what kind of data could be used for experiments. So, when looking into forecasting, we're looking at going to give a bunch of suggestions of different forecasting and trying to understand how it could be useful, or even if you'd find that useful. Would forecasting demands be of any use?

General Manager: Yeah, it would have an effect on what you're trying to do as far as if it comes at a time where you're able to adjust your crop volume, yes, it would have value.

Interviewer: Would forecasting-

General Manager: Were you talking crop forecasting? Or tell me exactly what we're talking about.

Interviewer: It could apply in any part. It could be on the supply side or on the demand side.

General Manager: If we know ahead of time on the demand side that there's going to be a large demand for overall volume, then maybe we don't finish heavy on a stone fruit situation. If we believe that there's going to be a big demand on citrus for medium to larger size fruit, we don't thin citrus at all, to speak of. So, it may mean that we've got to plan our harvest a little bit later to try to gain size on the fruit, so it would move your harvest timing back a little bit. So, yeah, all of that ties together.

Interviewer: What about weather?

General Manager: You know, weather is one variable we have no control over. We work from history on anticipating freeze periods on citrus, hail periods on stone fruit, just never knowing exactly what's going to happen. Forecasting weather is really a guess, so I don't bank much on whether you react to it.

Interviewer: Okay. What about water availability?

General Manager: Definitely. You have to know if you're going to be in a short water supply situation, what blocks you may choose not to farm. That would impact the time, money, energy you would spend on those crops, those blocks for all inputs on developing your crop. So, yes, water forecasting is important.

Interviewer: What about forecasting produce quality or product mix?

General Manager: You know, we always try to grow to a standard quality. Usually, the marketplace, again, the market demand is going to dictate what they'll accept. We historically have found that they want a higher quality product, and so we farm to that. We don't necessarily choose at SunWest to grow to an export standard, which requires more cost input, but we always form to a standard to achieve a consistent quality product to meet the market that we're aware of and we participate in.

Interviewer: Would getting information and data about the economic environment overall in the country help, and would it change anything of what you were doing?

General Manager: Yes. If we know that there's a downturn in the economy and that the expectation for consumer demand for the products that we produce is going to be diminished, yes, it would affect our approach to the market and hat we plan on harvesting, packing and selling.

Interviewer: Would knowing the yield of your competitors in the general area help?

General Manager: If we could obtain that information, yes, it would give a better view of what the actual crop volumes are. We get it through industry groups today, with a bit of a jaundiced eye, not trusting that we're getting full truth on the information that is shared. If we knew accurately what other people were doing and volume, if everybody in the area was finding that they're harvesting more than what was forecast, it may affect what we do as far as selling the product. So, yes, that would be valuable information.

Interviewer: What about the yield and cost per block?

General Manager: For our competitors?

Interviewer: Or just for yourself, being able to forecast that.

General Manager: Yeah. Oh, yeah. Definitely, not only for the current crop year, but also deciding whether a block is going to continue to be farmed or going to have to be replaced.

Interviewer: Is that something that's currently forecasted, or is...

General Manager: Not necessarily. I think we look back and we take a look at the history and say, "Okay, this block the last few years has not returned produced or returned the dollars back to the farm," so then we would make a decision whether to pull it or keep farming it.

Interviewer: Going into the cost of packing, is that something that's forecasted, or is that only looking back as well?

General Manager: Well, historically, we anticipate an increase on packing material costs every year of 3 to 12%. We throw 6% out as an average. It is affected by the customers that we choose to do business with, be it a Walmart or be it a high end retailer who has to have his own special packaging, which is going to cost more, that all has to be factored in, yes.

Interviewer: What about the labor costs?

General Manager: Well, we know that we're working on a mandated increase through 2023. So, yes, we need that information. We have a base pay that's based on that per our mandate, but then there's premium pay for certain positions, and then whatever the competition is in the marketplace for labor today, it's not been greatly affected by labor shortages, but it could be. So, yes, that information is important.

Interviewer: And the majority of this information is the raw data is generated from your pack-out reports, right?

General Manager: Yes, it is trying to derive a per unit cost of labor. We don't necessarily incorporate the cost of the packaging materials into that, because we're looking at that as a fixed cost, the variable becomes labor input against output of units, so that's the one we focused on mostly.

Interviewer:

Interviewer: How happy are you with your ability to forecast?

General Manager: Oh, mosy is from history and anecdotal current information. I can guess fairly well what the market's doing. I do use some USDA market information on supply demand and pricing that's available. The grano metrics is something that I've been looking at this year. It seems to give me some guidance, but I don't have a real formal process for feeling like I've got accurate dashboard information to look at and make decisions from.

Interviewer: What would you like to be able to forecast that you're currently not forecasting?

General Manager: That's a tough one. You know, if we're going to really look at being able to pull out the crystal ball and make a forecast and where we're going to end up in a year as we go through the seasons day to day, whether it's stone fruit or citrus, we're just kind of riding the market and not knowing what the outcome is until we get to the end of the season. If we could map out three, four weeks in advance what the market is going to do, we pretty well know what our supply availability is, whether we choose on citrus to harvest it then or wait, would give us some opportunity to maybe maximize the return to the farm stone fruit. You got to pick it when it's ready, so there's really not a lot we can do other than say, "Okay, we're going to quit packing a certain size because it's producing negative results." So, the information, if you can get it and lay it out ahead of time, it gives you the opportunity to make harvest decisions and/or packing and marketing decisions. So, I don't have that right now.

Interviewer: So, that would be the data that you'd want to have the currently don't.

General Manager: Yeah. Yeah. Yeah, we can forecast volumes on the stone fruit. The sales manager does that now, a three week forecast by product and size. Then if we were able to anticipate where the market's going on top of that, we might say, "Okay, sixties and smaller, we're going to quit packing because we're going to go to freezer, we're going to just send it to juice or leave it in the field because it's a cost issue." So, yeah, that would be helpful.

Interviewer: You mentioned that you heavily rely on expert opinion to make decisions. Is there anything that you think could be done to make the expert opinion you rely on more accurate?

General Manager: Oh, probably the biggest thing is, again, it's the market and what our packing forecast is and what the FOB sales by product is. That's hard to do. I think we could probably do a fairly good job at it because we've got a high percentage bar or product that's contracted. We've got the fixed pricing in place to be able to anticipate where it's going to go, as long as we don't see prices move off of contract. Then it's what's remaining that would be free market fruit that we really have to take a look at what percentage of our volume is in that classification and what do we anticipate the market doing in getting a return back on that fruit. We're probably, I'm going to just guess, on stone fruit, maybe 70% contracted between Walmart, Costco, Trader Joe's, Aldi's, which leaves us in a pretty favorable position in a normal crop volume year to better forecast our outcome versus those that might only be 30% contracted playing the open market. That's very risky.

Interviewer: Okay. Okay. That was the phase two one, and hopefully we'll get back to you in a week.

General Manager: Excellent, Jeremy. Good to hear from you. Hope everything's going well on your end.

Interviewer: Yep, thanks very much.

Phase 3

Interviewer: Okay. So for phase 3, I took the input that everyone made and we put together a possible predictive model that if the data was available, something that could be built.

General Manager: Okay.

Interviewer: And that's what I sent over earlier?

General Manager: We've got that in hand. Yes.

Interviewer: So I just want to go through each one of the modules and get your opinion on how valuable it would be. So the first module we'll be looking at is field forecast. And we're talking about the expert opinion of what's in the field? What the quality is? And how we pack in? From my understanding, there's normally like a three week forecast that's normally generated and talked about in your planning meetings.

General Manager: Right.

Interviewer: If that was codified in a way that you could track the reliability of the forecast versus actual and how the forecast changes over time. Would that be information that'd be valuable?

General Manager: Absolutely. Yes.

Interviewer: Okay. And why currently isn't that being done?

General Manager: I think it's a follow-up stage to compare forecast to actual, I don't know that we have an automated mechanism in place nor a person assigned to really stay on top of that.

Interviewer: Okay, great. Because that could be used probably to create a dashboard to see how good each of the field managers is doing.

General Manager: Yeah. That is a matter of measurement or accountability is important as well, because your information is only as good as what's provided. And so yes, that has to be done.

Interviewer: The next module we'll be looking at is the field weather. And actually this could be data generated from either the weather service or using localized sensors that would then track weather data back to the block level, so that if there's variability, you can then go back and see what variable it really was. And then also if there is weather that's occurring or forecasted, it could be predictive of quality or yield issues.

General Manager: Sure. Supply and quality are the two major variables affected and so there's a difference in citrus and stone fruit, but in either case it really is supplying quality. And so that information is very important.

Interviewer: Is that something you're currently tracking at all or it's just basically general feeling of it?

General Manager: It's nothing that we use as a dashboard predictive in processing. It's anecdotal, it's in meetings that we discuss when it's winter time rain or freeze, in the summertime it's heat and the possible impact on quality or length of time that crews would be in a field, which would affect a supply on any given day. And again, not doing it, what I would consider as a disciplined routine.

Interviewer: So you think there'd be value in creating a routine out of it?

General Manager: Yes. Absolutely.

Interviewer: Okay. The next module we're looking at is field management, which would include pruning and just keeping track of every single thing that happens to a field that it's including fertilizing, tilling, any type of tree management.

General Manager: Sure. Again, it has an impact on supply and quality. And so you need to take a look at what your input variables are and what differences may be between blocks or decisions made to prune at certain times or thinned to a certain level, on the stone fruit and also on the citrus level of pruning, done to the trees and what the resulting quality of fruit will be. So yes, very important.

Interviewer: As far as pruning goes, is there a way that a system for codifying the level of pruning or what types of pruning done that could be useful?

General Manager: Yeah. Level and timing. What type of pruning on citrus, whether it's heavy limb pruning or just sucker pruning and the resulting impact on the following year's fruit. Stone fruit timing, whether we're doing summer pruning, what level or not doing the summer pruning and just doing the winter pruning. That becomes a matter of input cost to do one or the other or both summer and winter. And what type of pruning are you going after, scaffolds or just suckers and leaving the hangers for the fruit next year. How many scaffolds and how many hangers are you leaving. That all comes into the equation.

Interviewer: So there already is a system of being able to qualify each different type of pruning and communicate it with the field worker so it's just a matter of recording that.

General Manager: Correct.

Interviewer: Okay. That's a lot easier than we thought it was going to be. And the next part of that is also looking at water availability and how much water is given to the field. Which I guess could be, as after talking to someone else, could be a subfactor of the field management as well?

General Manager: Yeah. We've not got to the imposed requirements, restrictions of Sigma yet, but that's coming in. So that'll be even more critical when we run into limited quantities of water that we can apply to blocks.

Interviewer: Okay. The next module we look at is industry environment. And that will be the regional historical weather from major competitors and growing markets. So that could be looking at the weather in different areas, where [inaudible 00:06:11] is at, or even looking at Georgia, Florida in different markets where the [crosstalk 00:06:18].

General Manager: Mexico. Yes. If there's any other supply coming in at the same time period, what is the weather impact? It's an impact on supply. Supply and demand is what drives fresh produce market and those are important variables that we have to look at.

Interviewer: So once a couple years of data is analyzed and built into a predictive model, do you think that having a dashboard with the three or four weeks forecast with the weather service, that's basically saying how it's all going to have to affect things, would be useful?

General Manager: Yes. We need it for our local environment and also for the other potential competing areas. You mentioned Georgia, Florida. Georgia's more stone fruit timeframe. Florida could be stone fruit and citrus. Any other import markets that are bringing product into the US would also be important.

Interviewer: Okay. Is that something you're currently doing at all? Or is it more just anecdotal?

General Manager: Anecdotal.

Interviewer: Okay. The next area that we're looking at is industry environment, as far as demand is going. So in that we'd create some economic proxies and indicators of consumer behavior, looking at employment, unemployment, consumer confidence, spending on grocery items and historical sales. And try and come up with some modeling over time. So that looking at those factors, going into a season, you can kind of gauge what the demand is going to be. So you don't end up picking and packing for fruit that's not going to end up going out.

General Manager: Definitely a plus. There's a higher volume of business that's contracted today and so knowing what the consumer trends are going into it helps us in the effort of pricing the contracts and in anticipating with open market, maybe doing and so you might commit to, if it looks like it's going to be slow in the open market, committing to the contracted business in a higher volume. Those are very important factors in making the decision about what we're going to do with the crop.

Interviewer: Out of all of these modules, which one do you think is the most valuable?

General Manager: Well, that's a good question. Again, it all goes back to supply and demand and so which of the factors that are going to be most influencing on those two pieces? And so the consumer model is very important to that and field management.

Interviewer: Okay. On a scale of 1 to 7, with 1 being very difficult and 7 being very easy, how difficult do you think it's going to be to implement the field forecasting?

General Manager: 1 being easy?

Interviewer: Oh yeah. Which one did we say? Did we say field forecasting or field management?

General Manager: Well, you asked forecasting and 7 is difficult.

Interviewer: Which one did you say was going to be the most valuable?

General Manager: The field management.

Interviewer: Field management. So on a scale of 1 to 7, how difficult do you think that's going to be?

General Manager: We're already doing it. It's just setting it up in a more formal process, so I'd give that a 3.

Interviewer: Okay. So it'd be fairly easy?

General Manager: Yeah.

Interviewer: Okay. Is there a reason why it's currently not being done?

General Manager: Everybody's taxed on time to sit down and set up the models or collect the data to put it in reports. So it can be a value and that's just really the setup portion of it in a software application that is easily used. People can get paid by entering into a system if there's one that exists that gives them the reporting that they need.

General Manager: It's just, we don't have a vehicle today other than people using Excel and spreadsheets. And that does take a fair amount of time especially if you have to create a Excel spreadsheet model for each report that you need.

General Manager: So I would say, it's just a time constraint in the area. Your option is to go out and hire additional people to build those models and do the data entry or you're working from years of experience and that tends to be what we do in the industry is, "Okay, well, we got these variables that we're aware of and so the decision that we're going to make is based on what we know today being X, Y and Z."

General Manager: Somebody can come in with an effective, comprehensive model that is something that we can use as a tool we don't have.

Interviewer: So, do you think once that all's created, it'd be a process that people would accept?

General Manager: Yeah. It's really driven by the value and benefit of the results that come from that tool. And if done correctly and providing benefit, definitely. If we can go to a weekly report or a daily report that gives us some guidance on what we're looking at in terms of all of these variables that you've addressed in this chart, yeah, very helpful.

General Manager: Otherwise, again, it goes back to trusting people with experience and through communication with field and sales and operations. "Okay. What makes sense? What are we going to do?" That's kind of how we operate today on a day by day basis with communication.

Interviewer: Okay. Thank you very much. That's for concluding the interview.

General Manager: Yeah. If you can get that built, you've got something special. [crosstalk 00:12:42].

Interviewer: Yep. Okay. Thank you very much.