POLITECNICO DI TORINO

Master of Science in Engineering and Management

Master Thesis

Supply Chain Management: Cognitive Demand & Readiness Assessment

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TABLE OF CONTENTS

LIST OF FIGURES

1 INTRODUCTION

This thesis is based on the internship experience in JDA Software. JDA is the leading supply chain software provider. It was founded in 1985 and it is globally headquartered in Scottsdale, AZ. JDA helps companies optimize delivery to customers by enabling them to predict and shape demand, fulfill faster and more intelligently and improve customer experiences and loyalty.

The scope of this thesis is to demonstrate how new technologies are affecting the Supply Chain industry and, in particular, how Machine Learning is impacting the Demand Planning process.

In this thesis an analysis of Cognitive Demand solution, JDA's reaction to this wave of changes, is performed focusing on: its definition, its weaknesses and strengths, its architecture and the ecosystem of partners involved, a market and competitors analysis and the results obtained from the Proof of Concept.

A model for understanding the level of maturity of a company's Demand Planning Process is developed. The readiness in implementing JDA Cognitive

Demand solution is assessed through the "Cognitive Demand Readiness Assessment", based on 85 questions concerning different focus areas.

This tool allows companies to identify the gaps between the level of their actual process and the desired one and provides them a roadmap to fill these gaps.

2 SUPPLY CHAIN EVOLUTION: TOWARDS A NEW SHAPE

We are assisting to a transformation in the shape of the supply chain. A supply chain is made of all the phases associated in satisfying the customer request. The goal is to deliver the right item, at the right time, in the right place, in the right quantity and at the lowest cost possible. The linear model "Buy-Make-Move-Store-Deliver", used in the last few decades, where each step represents a separate and independent silo in which information is locked, is no longer competitive. We are in an Omnichannel world now. Omnichannel is a business model whose goal is to provide customers with a fluid and smooth buying experience whether they are buying online, by phone or in bricks and mortar store. This requires a higher need for personalization in what is delivered to a customer, thus deeper knowledge of the customer and stronger partnerships along the supply chain are required. The explosion of connectivity, globalization, focus on core competencies, consumer centric perspectives and other factors that will be investigated further on, have all led to needed changes in this mindset (Miller 2017).

Shifting from a traditional supply chain to a digital one allows to destroy the barriers and achieve more integration, interconnection, communication, agility and reliability. Digital supply chain puts the customer in the center and, through hardware and software, leverages on massive data availability to obtain synchronization among organizations. Digitalization has deeply affected the way people communicate and share information and it results in a disruptive effect on supply chain processes and industries. Capgemini Consulting defined digital supply chain as a way to obtain massive information and reach better collaboration, while Rapid, Scalable, Intelligent and Connected are its characterizing attributes according to Accenture (Büyüközkan 2018).

The new challenges that both manufacturers and retailers have to face, as a result of digitalization, are (Rotenberg 2015):

- More sophisticated customer expectations to satisfy;
- Rising pressure on reducing costs;
- Quick changes in product portfolio;
- Higher demand volatility;
- Development of new distribution channels resulting in more complicated logistics operations;
- Increasing supply chain risks.

Nowadays these are the main five principles of a supply chain delivering high performances (Rotenberg 2015):

1. Optimization: supported by the usage of new digital technologies and prescriptive analytics;
2. Synchronization: the goal is to go beyond the borders of functional silos, enhancing communication and coordination along the entire supply chain;
3. Agility: the degree of responsiveness of a supply chain has become crucial, this new environment requires to both act and react quickly;
4. Segmentation: it consists in prioritizing demand, supply and inventory for special customers or products;
5. Customer-centricity: design the entire supply chain starting first with the customer in mind.

The new representation of the supply chain is a network. A complex grid highly diversified, with multiple inputs, outputs and connection points. The goal remains the same: to be reactive and profitable, to respond effectively and efficiently to customer demand.

Figure 2-1 Traditional linear shape

Figure 2-2 New grid shape

Predictability is reduced since the social, political and economic worlds are influencing each other more than ever and including a wider range of people and culture. This new setting is known as VUCA, that stands for:

- Volatility: it expresses the speed and breadth of change;
- Uncertainty: it is the opposite of predictability;
- Complexity: it refers to the cause-effect relationships of a series of factors;
- Ambiguity: it deals with the complex comprehension and analysis of events that are unclear and that lack transparency.

This environment leads to the necessity of analytical methods based on data, especially for conducting demand planning processes, as we will better understand in the next pages (Blackburn 2015).

3 Industry 4.0 and Digital Supply Chain

3.1 Digital Supply Chain (DSC)

Digital supply chains make use of different innovative technologies and the most relevant for this study will be covered in this chapter. There are eleven main goals of DSC (Büyüközkan 2018):

1. Speed: it is the ability to respond fast to demand. As an example, both Amazon and Google are testing drones for delivery;
2. Flexibility: companies need to be agile. DSC allows to better predict events and react quickly and efficiently;
3. Global connectivity;
4. Real-time inventory: DSC enables to constantly monitor stock levels by using sensors and other new technologies. Understanding customer trends and better predicting demand leads to a better inventory management;

5. Intelligent: this term refers to self-learning and autonomous supply chains;
6. Transparency: the higher degree of collaboration, obtained thanks to DSC, among the different players in the supply chain, increases the visibility;
7. Cost-effective;
8. Scalability: digitalization makes it easier to scale the supply chain up or down;
9. Innovative: DSC are always up to date and ready for changes;
10. Proactive: DSC proposes possible solutions to address problems before they even happen;
11. Eco-friendly.

During the implementation of a DSC several challenges emerge. The greatest one is to collect so many data from various sources and assess their validity, then a sufficient level of planning, collaboration, information sharing and integration has to be reached. Furthermore, high volatility complicates demand forecasting. If a company is successful in overcoming these issues, the result is an improved customer experience. Having more information about customer behaviors, preferences and purchase patterns enhances the service level. A recent survey shows that, out of 2000 participants, more than one third is implementing digitalization and 72% believes to complete the process in five years. Companies that shift to DSC can increase their revenue by 2.9% yearly and gain 4.1% on annual efficiency (Büyüközkan 2018).

3.2 Industry 4.0 and New Technologies

3.2.1 Industry 4.0

Industry 4.0 is the term under which all the new technologies below are included and represents the integration of both virtual and physical worlds. The main pillar is networking. In the manufacturing sector it is known as the fourth industrial revolution. The first one driven by water and steam power, the second based on mass production and use of electrical energy, the third led by using IT and automate production and the fourth founded on the use of cyber-physical systems.

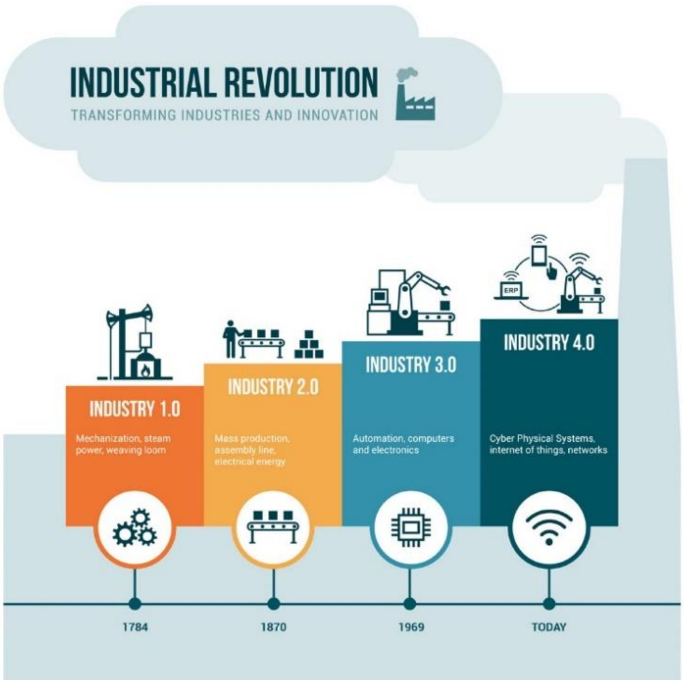


Figure 3-1 Industrial revolutions during history

Today we can clearly see how the new technologies are transforming every industry.

3.2.2 Artificial Intelligence (AI), Predictive Analytics and Machine Learning

It is possible to identify two moments in computing: the Tabulating Era and the Programming Era. In the first Era computers were basically calculators, in the second one they could also carry out logical operations and loops.

The concept of Artificial Intelligence has been in the air for years. In 1950 Alan Turing wrote the paper "Computing Machinery and Intelligence" that begins with the question "Can machines think?". In 1955 John McCarthy coined the term "Artificial Intelligence" referring to the possibility to create a machine able to simulate the human learning process (Miller 2017).

The period from mid '80s to late '90s is known as "AI Winter". Man-computer relationship followed the Hype Cycle, created by the Gartner Group, according to which there are five key phases in the technology life-cycle that are closely intertwined with the level of adoption (Gartner 2018):

1. Innovation trigger: a possible disruptive technology starts emerging, but there are no available products yet and the commercial appeal is not assessed;
2. Peak of inflated expectations: marketing actions, carried out through mass media, generate various success stories. Innovators start taking actions;
3. Trough of disillusionment: the first prototypes and attempts to implement the new technology fail and enthusiasm disappears. Investments go on just if companies react and manage to satisfy early adopters;

4. Slope of enlightenment: the advantages provided by the new technology are clearer and their understanding starts diffusing among the early majority. It is the moment is which the chasm is crossed;
5. Plateau of productivity: the technology reaches the broader market being adopted also by the late majority.

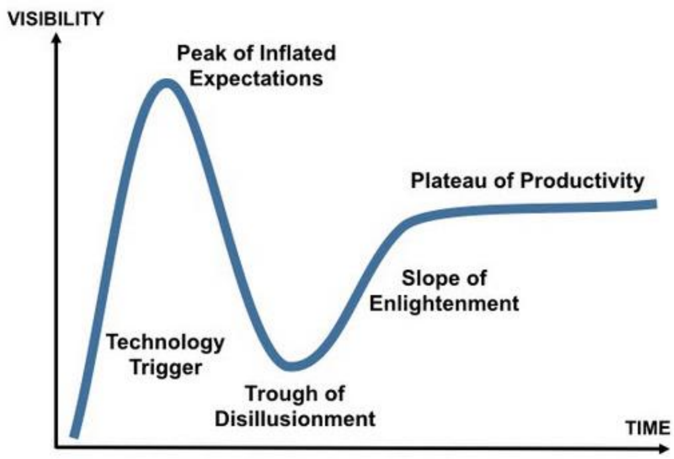


Figure 3-2 Gartner Hype Cycle

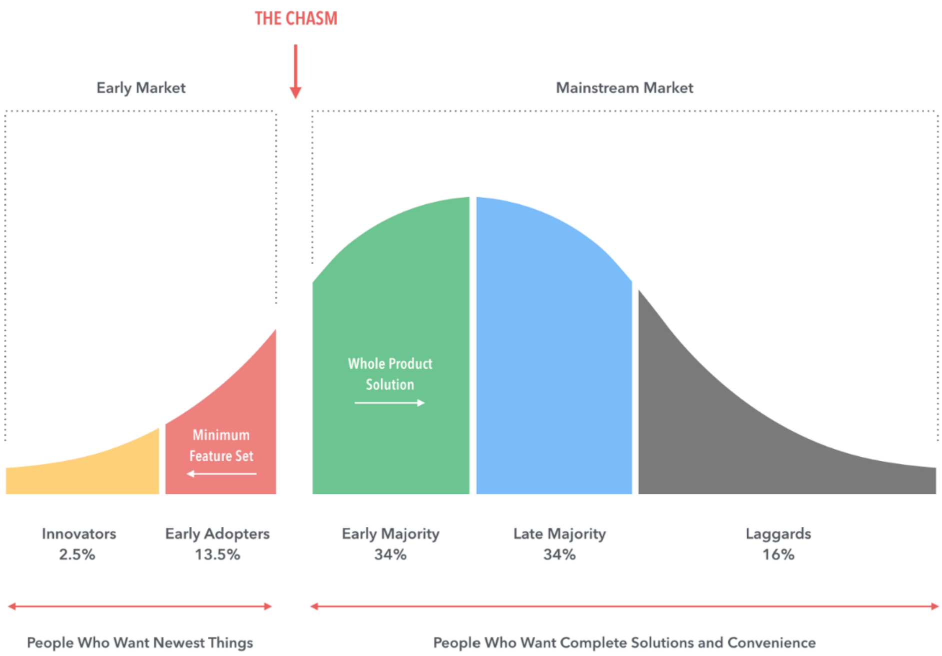
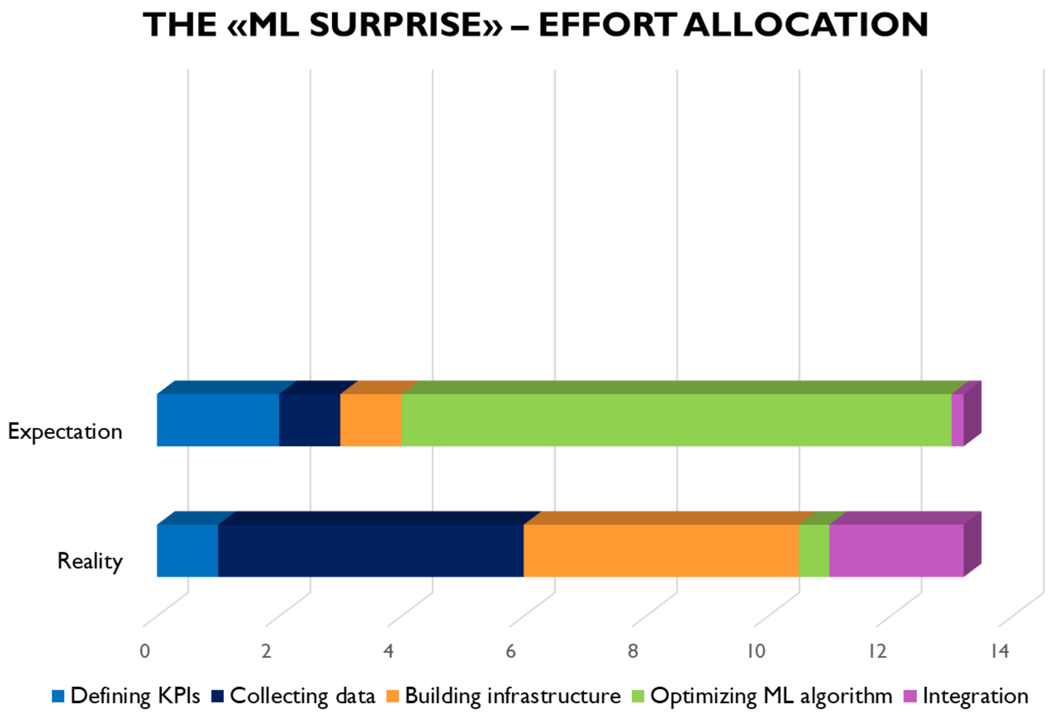


Figure 3-3 Crossing the chasm

AI is making prediction much cheaper and this is the reason why it is booming. This technology is also improving at a fast rate because its diffusion allows to gather more data and learn from them (Agrawal 2018).

During the internship at JDA Software, I had the chance to participate to a conference organized by INSEAD about the impact of AI and ML on society and businesses. Bruno Berthon (Senior Managing Director at Accenture Strategy) defined AI as "systems that perform actions that, if performed by humans, are considered as intelligent" and according to Kathryn Hume (VP Product & Strategy at integrate.ai and Venture Partner at ffVC) AI means "seeing a reasoning problem as a data problem and it shines in problems where the goals are understood, but the means are not". Malika Cantor (Global Lead at Google Launchpad) highlighted the gap between the expected effort allocation and the actual one with the following graph.



Predictive analytics allows to interpret, forecast and manage business processes through a technique based on data. It is largely used for inventory management and demand forecasting. The methodologies that predictive analytics employs are: traditional statistics, data mining and machine learning.

The main challenges of forecasting are (Fusionops 2016):

- Gathering data and develop statistical models is a time-consuming activity;
- Statistical models are not available in a big number;
- Need for programmers and data scientists with deep knowledge;
- The aggregated level is used as basis to measure forecast accuracy.

Machine Learning exploits the possibilities offered by cloud computing and big data to generate a much more accurate forecast that can be seen at any degree of granularity (even product-location level).

Fusionops provides an example of how forecast accuracy improved shifting from Exponential Smoothing (see Fig.3-4), a traditional forecasting model, to LarsLasso Cross Validation (see Fig 3-5), a Machine Learning algorithm. The comparison is based on the computation of the Mean Absolute Percent Error (MAPE), it calculates the difference between the forecasted quantity and the actual one.

$$MAPE = \sum_{1}^{n} \left| \frac{Forecast - Actual}{Actual} \right| \times 100$$

In the first case the MAPE is equal to 21%. Traditional method (orange) did not get the decrease in sales (blue) and led to an inaccurate forecast (green). While, in the second case, MAPE turns out to be 3%. Machine Learning succeeded in following the historical sales curve, leading to an accurate forecast (green).

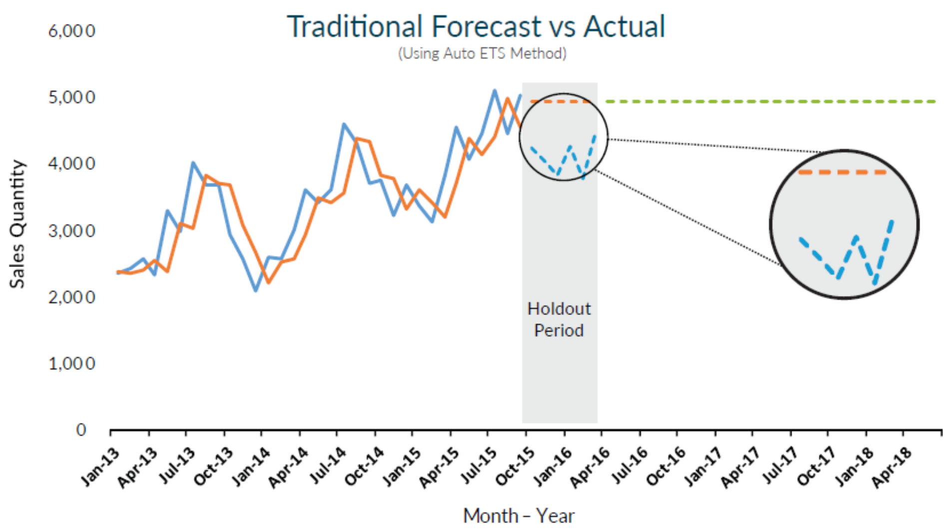


Figure 3-4 Traditional forecast

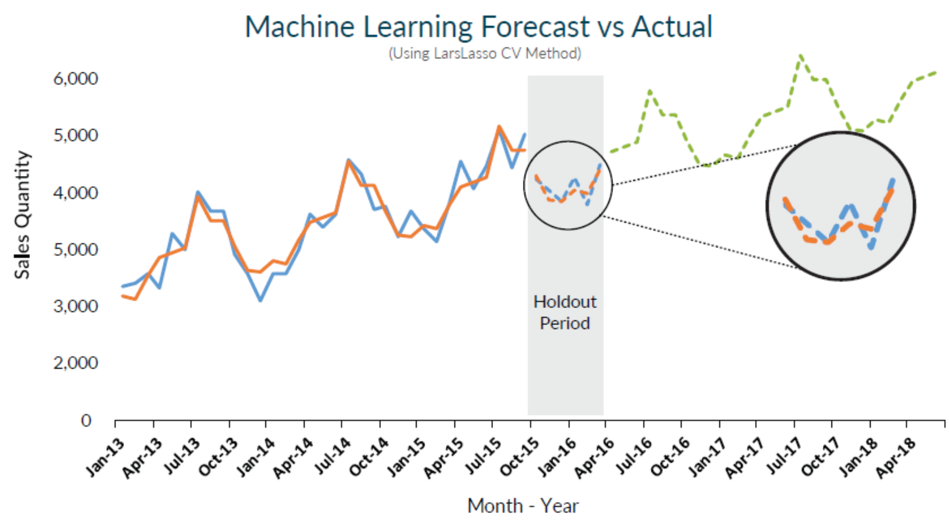


Figure 3-5 Machine Learning forecast

Machine Learning provides the basis for cognitive demand. It consists in the exploitation of past experiences and big data to predict future outcomes. The big data field represents both a threat and a chance. The chance is the possibility to access a huge amount of data, while the threat is to deal with the four sides of big data, referred to as VVVC (Blackburn 2015):

- High volume;
- Originated with extreme velocity (almost real time);
- Huge variety (different formats, both structure and unstructured);
- Deep complexity.

Trade-offs are required since more data entails less privacy, more velocity means less accuracy and more autonomy leads to less control.

The journey to obtain benefits from Machine Learning is an evolutionary process: first learning how to crawl is needed, then how to walk and ultimately how to run (Institute of Business Forecasting & Planning 2018).

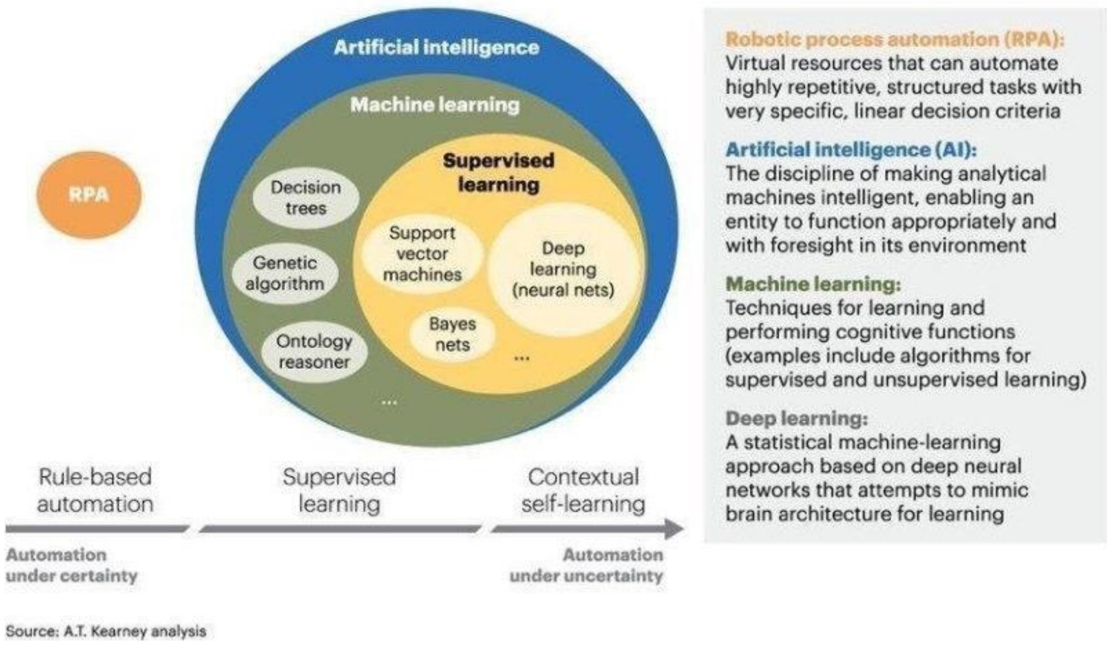


Figure 3-6 Artificial Intelligence and Machine Learning

3.2.3 Cognitive Computing

Cognitive computing refers to probabilistic systems that can learn, reason and cooperate with humans. Traditional systems need to be programmed in advance and they work based on predefined rules, this prevents them to keep up with big data pace. Cognitive systems, on the other hand, allow much more flexibility as they process real-time data and can take into consideration new relevant elements, such as context or concepts like “probably” or “sometimes”. They can solve complicated issues coupling together humanlike thinking and advanced mathematics (Enterra 2018). They are based on data, both structured and unstructured. Today we are generating 2.5 exabytes of data and the 80% is dark, this means that is contained in books, emails, social networks, images and so on. The problem is given by the unbalance between the amount of information and our ability to read it, this is the reason why we need cognitive systems.

Cognitive computing makes use of predictive analytics to:

- Navigate an enormous amount of complex information in an extremely small time;
- Offer hypothesis for evaluation and learn by experience;
- Continuously build knowledge and improve the cognitive system over time.

It is possible to identify five core capabilities of cognitive systems (Miller 2017):

1. Establish a stronger engagement: thanks to the huge amount of data they can process, they can identify which factors really matter in engaging a

person. Their continuous learning ability allows them, with time, to become more anticipatory and empathic;

2. Scale and augment expertise: they can learn and transfer complex expertise making available to people their know-how;
3. Instill cognition into services and products;
4. Allow cognitive processes and operations: continuous learning, improved forecasting and better operational efficiency lead to faster decision making;
5. Boost exploration and discovery: the application of cognitive technologies enables the identification of schemes, links and hypothesis that would not be possible to uncover using traditional programmable systems.

3.2.4 Internet of Things

According to Cisco Systems Inc., 50 billion of devices will be connected by 2020 (Miller 2017).

Internet of Things is the technology that allows us to sense and govern the physical world. It refers to objects, connected to internet, that can send and receive data. It is a piece of a bigger network of people, data and processes called Internet of Everything. It includes: Internet of Information, Internet of Systems, Internet of People, Internet of Places, Internet of Things and Internet of Virtual Entities.

3.2.5 Cognitive Manufacturing

The application of cognitive technologies to manufacturing takes the name of Cognitive manufacturing or Smart manufacturing and gives the possibility to enhance (Miller 2017):

- Equipment maintenance by preventing delays, increasing visibility and speeding up repairs;
- Factory operations;
- Product design;
- Quality by modeling and verification of design, as well as early quality diagnostic;
- Supply chain management by allowing higher flexibility;
- Employee safety and expertise;
- Sustainability by reducing energy consumption through real-time monitoring and options to decrease cost and impact on the environment.

Having a cognitive strategy is the key element to be successful and can be divided into four main steps (Miller 2017):

1. Identify the value and scope: not all problems can be solved with cognitive solutions. Companies need to be ready and to have the right infrastructure to derive benefits from cognitive technologies. Once the readiness assessment has been conducted, the cognitive vision and roadmap need to be established and updated regularly;
2. Establish the base: since cognitive solutions need to be trained, this implies the engagement of time and people to set the couple “question-answer” that

allows the system to learn. Companies should verify their employees' knowledge level and should fill the identified gaps. Apart from the right skills, another fundamental requirement is the right attitude and mindset. These can be developed and supported with a good change management strategy, as we will examine more in depth in the designated section. Furthermore, the huge amount of data required to make cognitive systems work effectively, can be obtained by developing partnerships with other companies;

3. Manage the change: change management is essential and chapter 4 deals with this topic;
4. Keep track of the benefits through periodic reviews.

4 IMPLICATIONS OF THESE NEW TECHNOLOGIES

4.1 Need for Change Management

People are the main resource for a company. The transition to digitalization will be a failure without the right involvement, support, mindset and attitude. Data and tools are secondary, the key is to have motivated people who really believe in changing the organization. Success is not just the result of a good technical implementation, but there are various factors playing an important role. The main cause for slow digital implementation is the lack of awareness among employees and stakeholders. Even the best forecast model will not deliver any benefit to the company if managers do not accept it and integrate it into the decision-making process. Predictive analytics must be considered a complement tool to expert judgement, not a rival. There is a gap between people intentions and their readiness for change, 75% of retailers and manufacturers recognizes the importance of online data but the majority of them still prefers to use phone and fax (Büyüközkan 2018). Managing people, their expectations and fears is the key for a successful change.

These are the six main steps (Blackburn 2015, Miller 2017, Aykens 2018, CMO Council 2018):

1. Assure executives involvement and active participation: managers should participate actively in infusing enthusiasm among all the stakeholders and should serve as an example for them. Real change starts from the top, it is a top-down process;
2. Communicate the results of predictive analytics to managers in a clear way with opportune interfaces, as well as an easily understandable jargon;
3. Spread the cognitive vision inside the company and develop a formal strategy and shared goals. Even if the transformation starts from the top, it is fundamental for each function to understand its role in the organization's strategy;
4. Constantly educate stakeholders: as the system learns, stakeholders need to be trained accordingly;
5. Support and facilitate the communication among stakeholders overcoming the silo effect;
6. Create cross-functional teams, with different interests and different points of view. As Angela Hsu, Vice President of Marketing and eCommerce at Lamps Plus, says "We often find insights not only in the data that is untapped, but in taking a different look at the same data".

The Gunasekaran et al. study (Gunasekaran 2017) defines big data and predictive analytics (BDPA) assimilation as the last step of a three phases process:

1. Acceptance: it is linked to the stakeholders' awareness about BDPA;
2. Routinization: the ability of a company to adapt and reshape its structure and systems to welcome BDPA;
3. Assimilation: degree of BDPA diffusion within the enterprise.

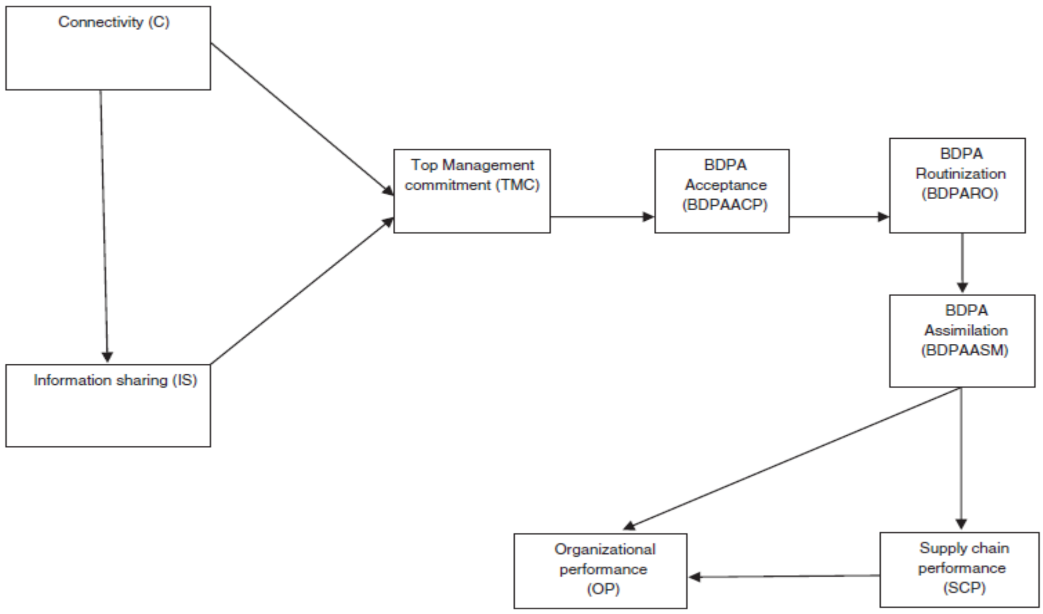


Figure 4-1 Model proposed

BDPA assimilation guarantees improved supply chain performance and organizational performance. According to the study and based on the resource-based view, connectivity and information sharing are resources, while BDPA acceptance is a capability. The importance of management involvement is again stressed out since statistical analysis show that, starting from connectivity and information sharing, BDPA acceptance is reached thanks to the mediation effect of top management commitment. It is in the hands of managers to coordinate and orchestrate resources to exploit new technologies benefits.

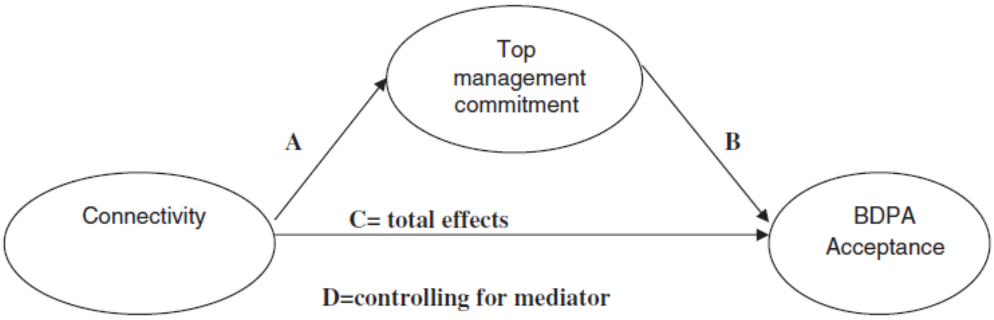


Figure 4-2 Mediating effects of top management commitment

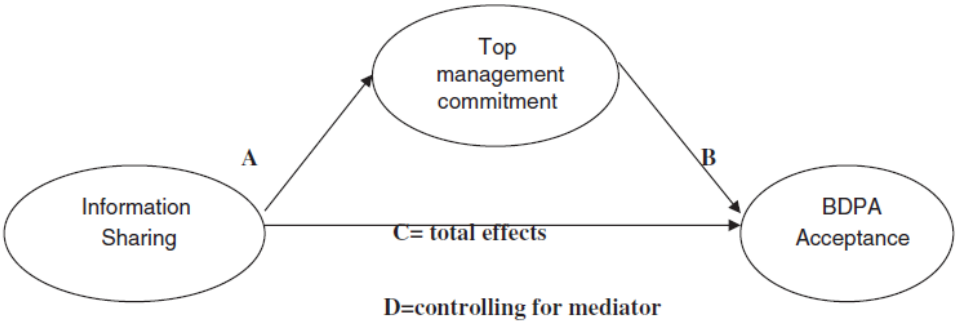


Figure 4-3 Mediating effects of top management commitment

Kübler Ross change curve illustrates the seven phases charactering organization and culture changes that are (Cleverism 2015):

1. Shock: employees are "shocked" because they are pushed out of their comfort zone and they have to work in a different way from the one they were used to;
2. Denial: it is a defense mechanism, they try to convince themselves that nothing is changing;
3. Resistance: they cannot deny change anymore and, for this reason, they feel anger and resistance;

4. Depression: when they accept that they need to adapt, they decide to do it just for what they think is important and not based on scientific basis. This leads them to failure which makes them depressed;
5. Engagement: this phase is the “turning point” that will make the difference between failure and success. Employees start to change their mindset and behavior, becoming more suitable to change and feeling more involved;
6. Decisions: they see the results of their new attitude that are better than what they expected so their morale keeps on rising;
7. Integration: change is completed and successful, employees are happy and willing to share their positivity with colleagues who are behind in the changing process.

Understanding this change cycle can help companies to overcome the “valley of despair”. This is the hardest point, where most of the companies remain stuck until they are forced to abandon the change process. The goal of an efficient change management methodology is to minimize this dip.

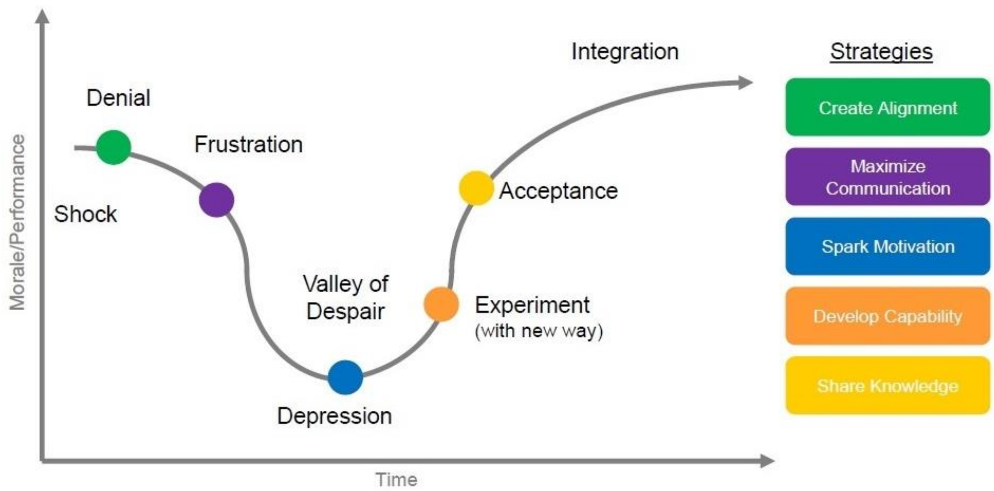


Figure 4-4 Kübler Ross change curve

4.2 Impact on Demand Forecasting

Being able to predict demand changes is crucial to manage supply chains, since both operational and tactical choices concerning scheduling, logistics, warehouse management and production planning depend on the forecast. Under-forecasting can drive to stockouts resulting in extra costs due, for example, to the need of arranging rush shipments or even to lost sales. On the other side, over-forecasting increases inventory carrying cost and can cause products to be sold at discounted prices. The increased level of competition and customer expectations accentuates the need for accuracy. The need to include exogenous variables in the forecast is emerging. Exogenous variables can be internal, such as demand for analogous items or aggregated demand at different levels, but also data belonging to the public domain, especially internet (Blackburn 2015).

As seen before, forecasting in a VUCA environment is highly challenging. In the first place, the effect of volatility (for example faster product innovation, shorter product life cycles and accelerated shifts in customer desires) is to have a smaller amount of historical data. Secondly, uncertainty leads to neglect possible advancements presuming they are just “noise”. The third element, complexity, makes hard to analyze a big number of factors and their intricated relationships. Finally, the recognition of covariates gets complicated due to ambiguity.

Demand forecasting models have traditionally used a single historical time-series as the basis for forecasting future demand. This time-series is traditionally point-of-sale units, shipments or orders. Leading companies augment the sales history with causal information, typically related to variables known and controlled by the enterprise (such as price or promotion tactics). Demand management practitioners understand and admit that forces external to the enterprise play a significant role in shaping demand, but still few companies are able to incorporate them in their forecast.

In the past, external forces have been excluded for three primary reasons (Madhavanur 2018):

1. Data availability: collecting external influences was an extremely manual and error prone process;
2. Modeling limitations: traditional regression modeling techniques have limited power to explain many, often intertwined, variables;
3. Technology limitations: running models with many variables, on a frequent basis, for a large enterprise was often infeasible or so computationally intensive that the costs were prohibitive.

Today there is significant pressure on software providers to deliver demand forecasting solutions that incorporate many big data signals. The barriers that existed in the past are largely gone. Vast amounts of structured and unstructured data are available frequently and digitally, eliminating the painful manual efforts of the past. Furthermore, the available signals are exploding at an exponential rate. IoT delivers an endless stream of potential demand insights as well as demand shaping opportunities. Machine Learning and AI algorithms now replace traditional regression techniques and possess the ability to distinguish the signal from the noise in input variables (Madhavanur 2018).

The use of AI and Machine Learning applied to this field allow to overcome one of the main issues in demand forecasting: human biases. The study conducted by IBF (Institute of Business Forecasting & Planning 2018) classifies 8 different types of biases:

1. Trust me bias: it refers to the attitude people have to confirm their own beliefs by interpreting information influenced by their own ideas;
2. Overfitting: it is the tendency of people to continuously look for the best-fit model but with no guarantee that it will be able to produce a good forecast;
3. Anchor bias: it happens when people fall under the influence of someone else's opinion and tend to interpret data in a way that please them;
4. Innovation bias: it represents the tendency to consider each innovation as an improvement;
5. Black box bias: it is built on the assumption that everything that cannot be understood, must be wrong;
6. Complexity bias: it is the thinking that more complex are the inputs and better will be the result;
7. Modelling bias: it happens when people approach a problem having in their mind a series of biased preconceptions;
8. - (n=all) bias: when people keep focused on information that does not have an impact on the result of their analysis.

AI allows to incorporate both internal data coming from ERP, IoT, CRM and different systems and external ones coming from social media, news, weather, events and market intelligence. AI is able to catch real-time data and continuously learn, thus being able to suggest actions that need to be carried out. This way demand planners save time and can spend it on tasks that require more strategic thinking. Basically, the effect of AI and Machine Learning on demand forecasting is that they raise the scientific component, while in the past forecasting was more a matter of art (Glass 2018).

4.3 Importance of Data Quality Checking

As an effect of the great importance given to data, quality checking turns out to be a critical success factor. If the quality is poor data are not just useless, but even damaging as they can lead to wrong decisions. For a company the cost associated with low data quality is around 8-12% of revenues and could cause 40-60% of a service organization's expenses (Redman 1998). The outcome of a questionnaire diffused among 3000 business executives is that one out of five address data quality as the first obstacle in using new technologies based on data.

Based on the Total Quality Management cycle (Plan, Do, Check, Act) and on the DMAIC cycle (Define, Measure, Analyze, Improve, Control) defined by Six Sigma, Wang has developed a parallel between product manufacturing and data manufacturing (Wang 1998).

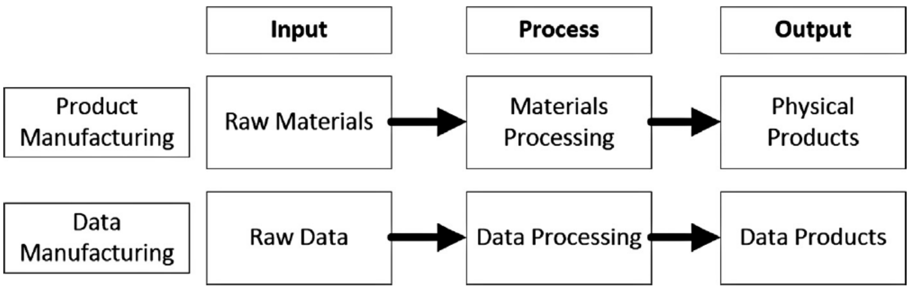


Figure 4-5 Analogy between product and data manufacturing

He states that the Total Data Quality Management (TDQM) cycle should be the tool to handle data quality. The limitation of the TDQM is that it defines, measures, analyzes and improves data quality but there is no control stage.

The first step is to define and measure data quality as “you cannot improve what you cannot measure” (Hazen 2014). Different studies and researches categorize data quality as “intrinsic”, based on attributes belonging to the data themselves, or “contextual”, based on attributes that can be interpreted in different ways depending on the context. The contextual dimensions are subjective and they are usually assessed through questionnaires, they range from relevancy, to accessibility, value-added, believability and reputation of data. On the other side, the intrinsic ones are four and well defined (Hazen 2014):

1. Accuracy: the maximum level is reached when data are exactly correspondent to the actual values. It is measured making a comparison between the values owned by the company and external ones known to be right;
2. Timeliness: it is possible to identify two subgroups. Currency is the time passed from the last update and volatility is the frequency with which the records are updated;
3. Consistency: data should all have the same form and structure. This dimension measures the level to which they correspond;
4. Completeness: the absence of missing data represents the maximum level of this dimension.

Data quality dimension	Description	Supply chain example
Accuracy	Are the data free of errors?	Customer shipping address in a customer relationship management system matches the address on the most recent customer order
Timeliness	Are the data up-to-date?	Inventory management system reflects real-time inventory levels at each retail location
Consistency	Are the data presented in the same format?	All requested delivery dates are entered in a DD/MM/YY format
Completeness	Are necessary data missing?	Customer shipping address includes all data points necessary to complete a shipment (i.e. name, street address, city, state, and zip code)

Figure 4-6 Data quality dimensions

By checking and controlling data quality during the data production process is possible to identify issues immediately and correct them or even prevent them.

4.4 Social Impact

What still needs to be investigated is the effect of these new technologies on society. Citing Elon Musk, “We need to be super careful with AI. Potentially more dangerous than nukes. With artificial intelligence we are summoning the demon”. Steven Hawking said “The development of full artificial intelligence could spell the end of the human race. It would take off on its own, redesign itself at a constantly increasing rate. Humans, who are limited by slow biological evolution, couldn’t compete, and would be superseded”.

A study conducted by “The Future of Employment” shows that improvements in AI and new technologies could put at risk 47% of American jobs due to automatization (Miller 2017).

The Institute of Business Forecasting (Institute of Business Forecasting & Planning 2018) released the results of a survey conducted on supply chain professionals where the question was which will be the competences and skills needed to forecast and plan demand in the future. The first three answers were:

advanced decision making, ability to summarize data and analytics. These are the characteristics that transform a person into a resource that cannot be replaced. With all the technologic advancements, the focus and interest of companies will shift from people who create the algorithms to people who can interpret them and with creative thinking capabilities (Lyall 2018).

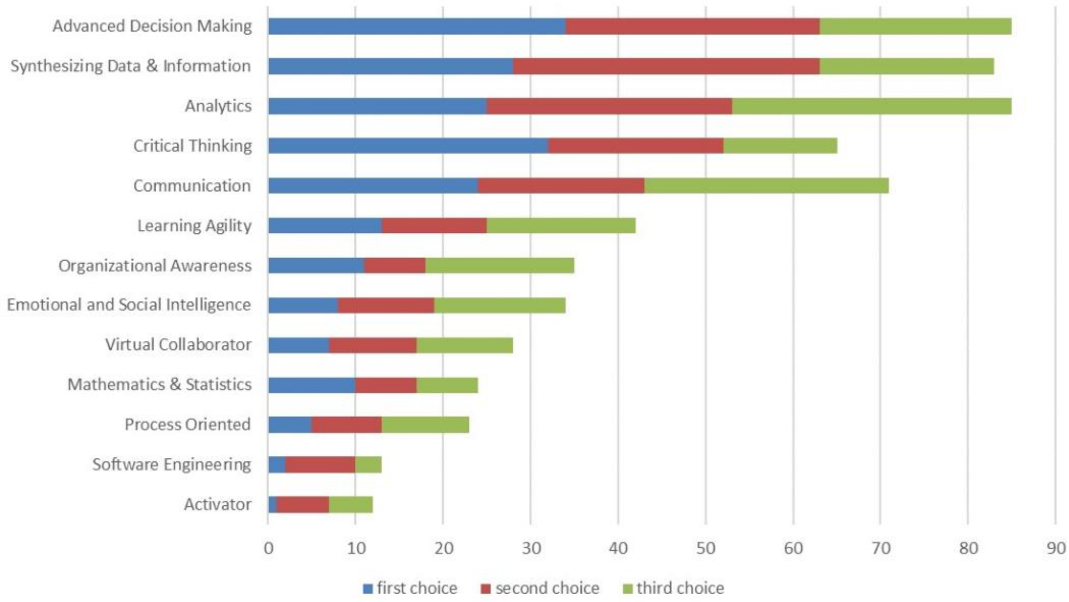


Figure 4-7 Survey results

The mindset of most companies approaching to AI is to figure out how to empower teams to achieve more, rather than how teams can be supplanted by machines. As we can understand, AI does not entail just a business change but also a societal one.

As Yves Bernaert (Senior Managing Director at Accenture Technology Europe) affirmed during the INSEAD AI Forum, there is no industry that is not touched by new technologies, especially AI. But nowadays few companies are approaching it correctly. It is not possible, for a company, to implement AI without thinking at the impact on its people. The way companies deploy AI systems must be seen as something improving people. “How AI can help people?” is the question companies should ask themselves. AI is not made to replace people, but to allow them to spend their time on more value-adding tasks.

4.5 Sustainability

Value can be created by taking into consideration how a company behaves in the social, cultural, environmental and economic environment. A company that cares about sustainability can increase its reputation, save costs and gain growth opportunities (Zhu 2017). The environment is affected by supply chains and in the latest years the importance and the awareness on this topic have increased. DSC is able to enhance its “green” capabilities (Büyüközkan 2018).

The U.S Department of Commerce defined Sustainable manufacturing as “the creation of manufactured products using processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound” (Miller 2017). The main challenge in this field is the incompleteness of data, KPIs and supporting systems, cognitive manufacturing is what grants the possibility to overcome these obstacles.

5 My Internship Experience in JDA Software

5.1 Who is JDA?

JDA is the leading supply chain software provider. It was founded in 1985 and it is globally headquartered in Scottsdale, AZ. JDA helps companies optimize delivery to customers by enabling them to predict and shape demand, fulfill faster and more intelligently and improve customer experiences and loyalty. It has more than 4600 associates in around 40 international locations and more than 4000 global customers use JDA unmatched end-to-end software and SaaS solutions to unify and shorten their supply chains, increase speed of execution and profitably deliver to their customers. JDA customers are 75 of the top 100 retailers, 77 of the top 100 consumer goods cos, 70 of the top 100 manufacturers and all 10 global 3PLs. Some of the companies are: P&G, Michelin, Continental, Coca-Cola, Lavazza, Dell, Chanel, Tiffany, Luxottica, Safilo, H&M, Electolux, IKEA, Metro, M&S, Loblaws, Starbucks, DHL, etc.

JDA is also the only company named leader in all five Gartner Quadrants (Supply Chain Planning, Sales & Operations Planning, Transportation Management, Warehouse Management, Retail Assortment) across supply chain and retail merchandising solutions and has been recognized by numerous industry analyst firms for product and corporate leadership (JDA Software 2018).

5.1.1 Porter's Five Forces

To analyze the industry in which JDA operates, the software one, and understand its attractiveness, I've used the Porter's five forces tool. It is made of three vertical forces which are threat of new entrants, rivalry among existing competitors and threat of substitute, and two horizontal forces which are bargaining power of suppliers and bargaining power of customers. Each force is analyzed in detail (Bartleby.com 2008):

1. Threat of new entrants: the strength of this force can be assessed by focusing on each of the main determining factors. These are:
    - Economies of scale: it is not possible to apply the economies of scale concept in this industry due to its nature. In fact, once developed the products, the production costs are almost null. Obviously, for the incumbents this is not a positive aspect;
    - Access to distribution channels: it doesn't represent a serious barrier for new entrants as internet is a virtually free distribution channel;

- Capital requirements: the main capital requirements in this industry are the development costs, which are quite high. No payment is made by customers during the development phase, thus return can be realized just once this stage is over and enough demand is generated. Hence this factor represents a high barrier for companies willing to enter;
- Switching costs: they represent the highest entry barrier. It is extremely complex for customers to switch from a software to another as it carries a series of implications. For example, integrating the new software with the already-existing architecture and training employees to use it. The high switching costs generate a customer lock-in effect, from which incumbents can benefit;
- Cost disadvantages independent of scale: they deal with proprietary product technology, learning curve effect, favorable access to talent, favorable location, brand and reputation, etc. This is a medium entry barrier.

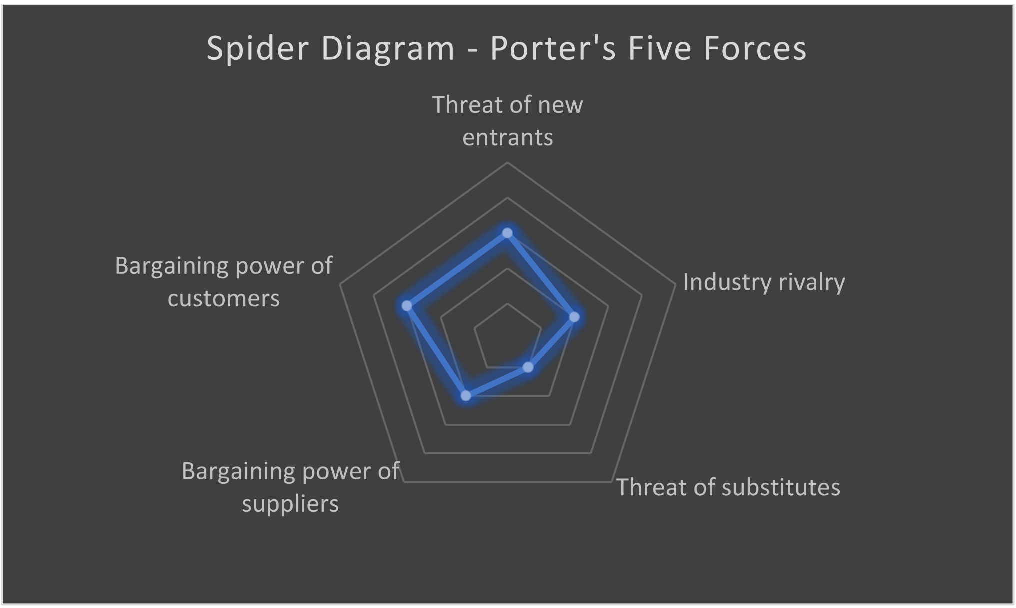
2. Threat of substitutes: it is really low since there is not a close substitute for software.
3. Rivalry among existing competitors: there is a trend in the industry of mergers and acquisitions. It creates a smaller number of "giants", hence reducing the number of competitors as well as the rivalry. Furthermore, switching costs are high, it is possible to apply differentiation strategies and

the industry is growing. All these factors contribute to lower this force, even if an increasing pressure on reducing prices is present;

4. Bargaining power of suppliers: in this industry the suppliers are mainly the employees. One of the key success factor is to attract, select and retain talented people. This is known as "the war of talent";
5. Bargaining power of customers: customers are powerful in the software industry. They have choices and are always more pretending, asking for higher quality at lower prices but, at the same time, switching costs are high for them. These factors make this force medium.

Below is a spider diagram graphically representing the Porter's five forces analysis.

In a nutshell, the threat of substitutes is the lowest force followed by industry rivalry and bargaining power of suppliers which are medium/low. The two medium forces are threat of new entrants and bargaining power of customers. Overall, software industry is growing and can be considered attractive.



5.2 JDA Approach to New Technologies and The Luminate Offering

Given all the major changes affecting the supply chain, as already seen in the previous chapters, JDA has reacted to keep its leading position in the field. They are developing a new set of products, called Luminate, based on cutting-edge technologies. Basically, technology will be put on top of existing core applications to enhance them towards JDA moonshot: the autonomous supply chain.

Luminate is the cognitive, connected platform that powers JDA's global supply chain network and community. Luminate's next generation solutions, which embrace digital technologies such as SaaS, IoT, AI and advanced analytics, allow companies to better predict and shape demand, fulfill faster and more intelligently, and create seamless customer experiences.

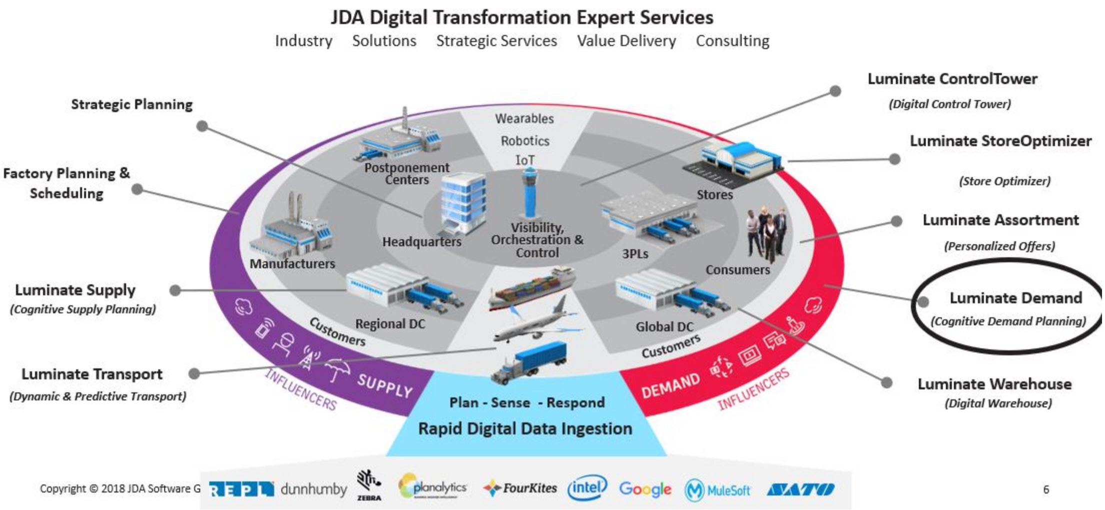


Figure 5-1 Luminate offering

The space ship looking picture above is meant to depict JDA's digital ecosystem, their new way of looking at the digital supply chain. The part within the saucer represents the familiar infrastructure of supply chain solutions: demand planning as well as production, warehouse, transportation and order management, all need to continue as they do today. The difference is the speed and automation with which decisions can be made, as well as the insights and signals it is possible to get from external sources. In the middle there is a new entity called the Digital Control Tower which is a virtual decision center that provides real-time, end-to-end visibility into global supply chains that will serve as the nerve center of JDA operations and identify bottlenecks and propose resolutions before they occur. Along the edges of the saucer there are purple and red bands representing information coming in from the world of IoT sensors, weather, events, news and social sentiments that are impacting a company's sales and disrupting its supply chain. Then, along the bottom, there is JDA evolving ecosystem of partners that they're working with. Finally, around the saucer are JDA Luminate solutions supporting the new vision.

5.3 JDA Cognitive Demand

5.3.1 Definition

Cognitive Demand has to do with how we see, how we do and how we learn. All these 3 processes are going to change. Cognitive Demand is the new JDA cloud-based SaaS application that allows to include external factors in the forecast. These new forecasts are presented as probability distributions enabling more informed decision-making.

Figure 5-2 Forecast as a probability distribution

Signals from SNEW (Social media, News, Events, Weather), IoT and other digital devices are incorporated and cognitive insights into the impact of these external influences are provided.

The primary customer need this solution solves for is lowering inventories. The picture below is showing the ratio inventory to sales, in a perfect world this would be 1:1. For almost two decades this ratio declined, however since 2011 inventories are on the rise. The proliferation of selling channels has introduced new demand volatility, against which companies hedge with inventory.

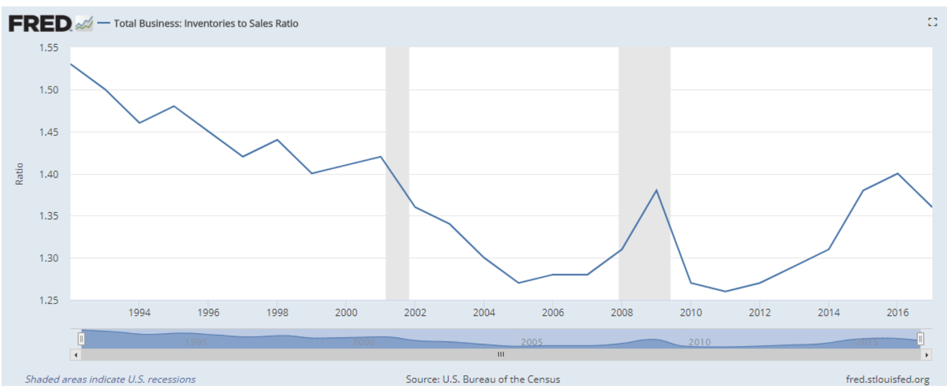


Figure 5-3 Inventory on the rise

Demand management and supply chain practitioners strive to eliminate unexplained variability. JDA Cognitive Demand helps to do this, it is done by listening to external signals and incorporating those that matter in real-time.

JDA is leveraging Machine Learning, big data and public cloud to deliver significant new value to its customers. This is done by integrating internal and external signals in a highly automated way, Machine Learning algorithms determine which signals matter versus which represent noise. Learning is applied from cycle to cycle, scoring outcomes and improving autonomous decisions in subsequent cycles.

From the user experience point of view, for existing customers, traditional JDA Demand solution is supplemented by new capabilities such as: dashboards to provide visibility to primary drivers of demand and exception-driven workflows.

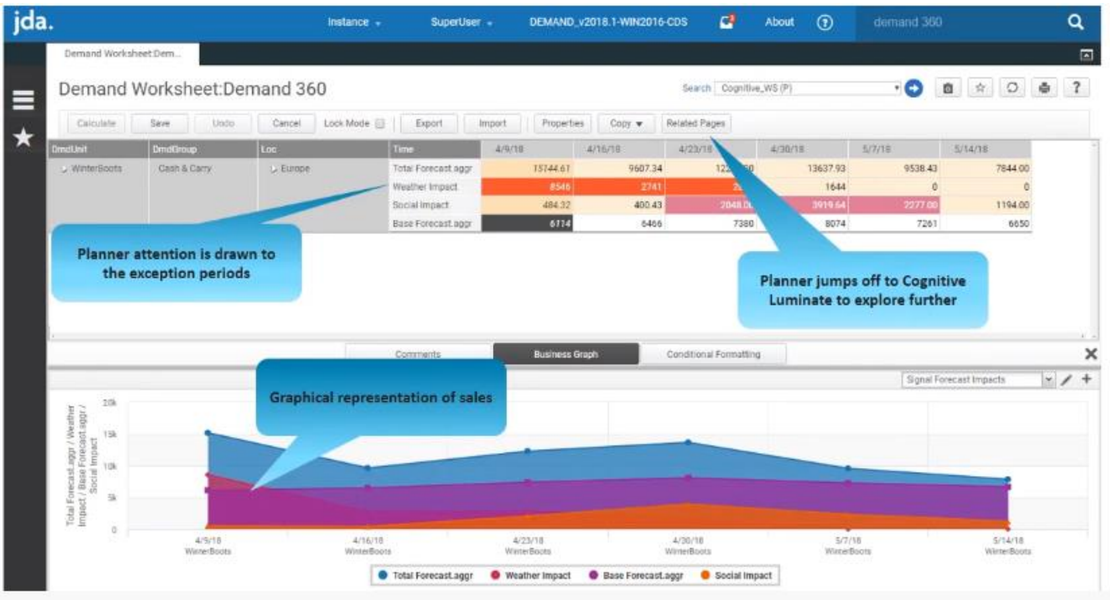


Figure 5-4 Traditional JDA Demand Worksheet

Figure 5-5 JDA Cognitive Demand dashboard

Graphical views highlighting insight to demand influencing factors such as weather, events, social media, news and promotions.

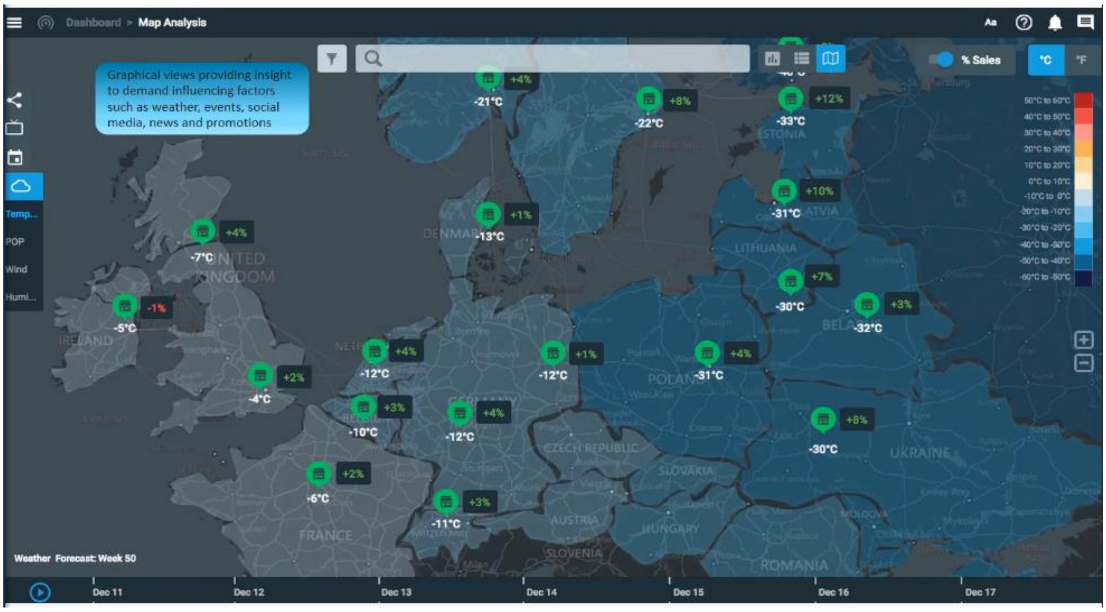


Figure 5-6 Demand influencing factors

Year-over-year views with information such as weather and social media trend.

Figure 5-7 YoY visualization

In conclusion, JDA Cognitive Demand leverages big data from within and beyond the enterprise bringing to light demand insights. With Cognitive Demand companies improve forecast accuracy while gaining a better understanding of customers buying behaviors.

5.3.2 S.W.O.T. Analysis

Having conducted interviews with different stakeholders within JDA and having read various internal reports concerning Cognitive Demand, I was able to identify the key Strengths, Weaknesses, Opportunities and Threats of this new solution that are shown in the table below.

INTERNAL FACTORS	
STRENGTHS (+)	**WEAKNESSES (-)**
• Improved forecast accuracy based on new insights (the goal is to reach 90% forecast accuracy with 90% automation) • Improved customer service with lower cost • Intelligent scenario planning • Increased revenues (estimated 5% revenue growth because of reduction in lost sales) • Reduced inventory (estimated 30% reduction) • Higher gross margin (estimated up to 500 basis point improvement) • Higher planner productivity (estimated planner productivity improvement of 25-75% with lower manual intervention from demand planners) • Less time spent on demand review	• It is still at an initial phase • It works well in the short term, tactical horizon more difficult • Mainly applied to A and B SKUs, further developments needed for NPI • Difficult to understand which data are impactful (data collection) • Difficult to determine the connection between data and effect on sale (ex. input from social media, how do you know how much demand will increase due to a twit about your product?) • Difficult to model the combined effect of two or more external factors (a lot of times externalities such as weather, events, etc. are correlated) • Data quality checking process is not fully automatized, manual intervention is still needed

• Improved understanding of demand drivers and customer behaviors • First mover advantage provided to customers adopting this new solution • Leveraging the cloud to solve demand problems that are traditionally expensive to address in an on-premise environment	• In order to scale the business JDA internal readiness needs to be assessed

EXTERNAL FACTORS	
OPPORTUNITIES (+)	**THREATS (-)**
• AI and Machine Learning are trending topics in these years • Inventories are on the rise and companies need to find solutions to this problem to survive • JDA has a strong reputation and can leverage on it to launch this new product • Easy to integrate Cognitive Demand for customers who are already using the traditional JDA	• It is an advanced technology and companies need to be ready to exploit the benefits • People can be reluctant to let go traditional ways of forecasting (resistance) • The perceived impact in customer organizations can be negative, for example they can fear a reduction of employees by the adoption of the new technology (social impact) • Some companies are still threatened to store their data on the cloud (cyber security)

Demand and Fulfilment solution • Possible partnerships with other companies with core competencies in Machine Learning and/or data providers • Collaboration with academia	

ANALYSIS SUMMARY
There is a lot of hype around digitalization, but it is more a matter of marketing than reality. Companies are still trying to develop new solutions and serve customers. This means that JDA is still on time to launch its new set of Luminate products, in particular the Cognitive Demand solution, and try to establish itself as a leader in this field. JDA should leverage on its existing customers who already adopted the traditional Demand and Fulfilment solution to test this new product and establish success stories to build trust among possible new customers. In this moment, there are three PoC (Proof of Concept) going on., the partial results are discussed in section 5.3.9. JDA should keep on developing and improving this new solution thanks to the research activity carried out by the Labs in Canada, but also building new partnerships. JDA already played this strategy, partnering and acquiring various companies with specific core competencies to gain a competitive advantage. This is explained more in details in section 5.3.3. What is important at this point is to not overinvest in new technologies, losing the "big picture", but keep focusing on core business and products that can be used as cash cows to generate funds to be invested in these new question marks that will hopefully

become the stars of the future. Last but not least, the key factor to successfully scale the Luminate/Cognitive Demand business is the internal readiness. As I experienced, there is a limited knowledge of this new set of products within the company and some of the people in charge of developing these solutions are quite reluctant to share information. For example, JDA could organize some trainings about these products to align the entire organization towards a shared goal.

5.3.3 Architecture

JDA established partnerships with various companies with core competencies in big data, cloud, AI and Machine Learning. The picture below shows the ecosystem of data partners.

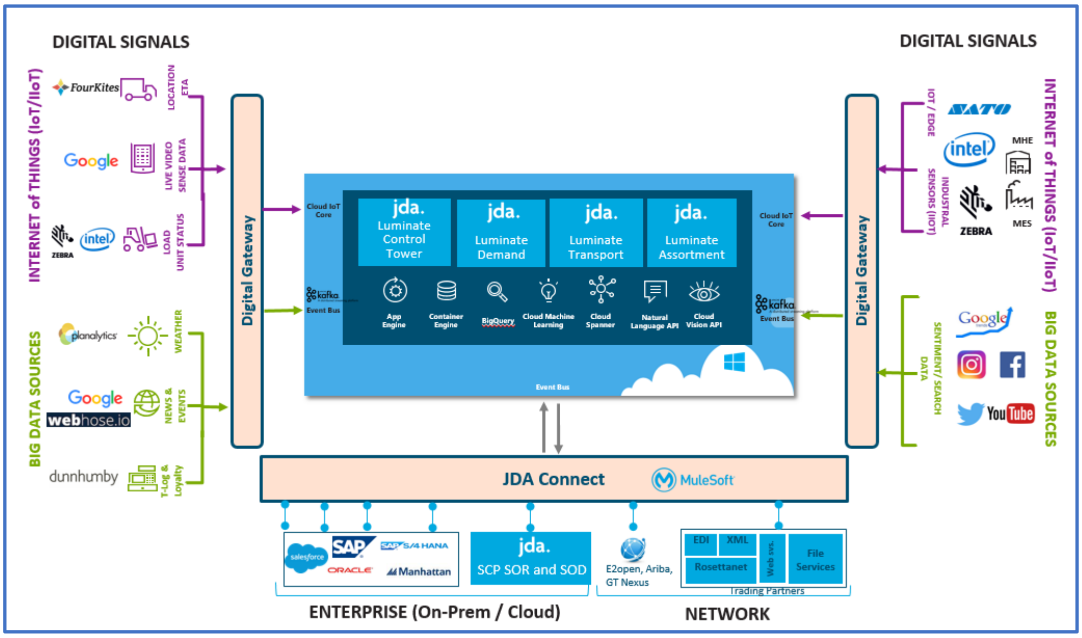


Figure 5-8 Ecosystem of data partners

For what concerns big data, the two main partners are Planalytics and Dunnhumby. Planalytics operates in the weather data niche market and it is the global leader in business weather intelligence. It allows companies to determine the weather impact on their business. They estimated that by “deweatherizing”, which means removing distortions due to weather factors, companies can increase by 2-6% their net income annually (Planalytics 2018). Dunnhumby is the world’s first customer data science platform and provides companies with competitive advantage by putting their customers first. Their study affirms that business focused on customer centricity outperform their competitors, with the top 25% achieving 3% growth in like-for-like sales and 7% increase in market share (Dunnhumby 2018).

Recently a new partnership with Microsoft has been announced to build cognitive SaaS solutions on the market-leading Microsoft Azure cloud platform. As Scott Guthrie, executive vice president Microsoft Cloud + AI Group, said “The powerful combination of JDA’s proven applications with Azure will empower customers to take advantage of real-time insights for smarter business decisions and profitable business growth”. Furthermore, JDA has explained that, thanks to a multi-year strategy, Azure will become the only platform for delivering all cloud and SaaS solutions. Building solutions on Microsoft Azure creates interesting opportunities for JDA customers to consume data at the edge.

All of this, together with the recently announced Blue Yonder acquisition, will make JDA vision for powering an Autonomous Supply Chain even closer to reality (JDA Software 2018).

Blue Yonder is the market leader in AI and Machine Learning solutions for retail. It has been acquired by JDA on August 2018 and it was founded in Germany in 2008 by the CERN Professor Michael Feindt. Blue Yonder solution allows machines to make objective and real-time decisions, lowering the risk of errors (maybe due to human biases, as already discussed in the previous chapters) and enabling companies to react faster to changes in the market and in customer preferences. According to Blue Yonder, with their solution retailers can benefit from an 80% out-of-stock rates reduction and a 5% revenue and profits increase (BlueYonder 2018).

5.3.4 How It Technically Works

Historically, sales history was fed in the time series forecast models to produce sales projections. The forecast is different depending on the product and JDA has a library of traditional algorithms that can handle every type of sales pattern: slow moving items that might sell once every few weeks, highly seasonal items, high volume items perhaps even with lumpy demand and brand-new items with no comparable history. This is a list of the current JDA algorithms and what they are used for:

- Regression based algorithms:
    - Fourier: it assumes that business changes at a constant rate;
    - Multiple linear regression: it refines models with multiple causal variables.
- Smoothing based algorithms:
    - Lewandowski: assumes business changes at an inconstant rate;
    - Croston: used for slow, lumpy items with sporadic history;

    - Holt Winters: used when seasonality and trend are changing at different rates over time;
    - Moving average: stable forecast based on recent past;
    - AVS-Graves: it handles intermittent demand patterns while incorporating seasonality.
- Others:
    - Attribute-based forecasting: attribute-based mapping extracts existing lifecycle curves, applies them to new forecasts and recalibrates as sales arrive;
    - Profile-based forecasting: simple, low touch algorithm that groups items together for the purposes of estimating seasonality.

JDA traditional solution has the capability to automatically choose the right forecast treatment for each location/item that will maximize forecast accuracy. This involves:

- Choosing the right level of forecast aggregation;
- Data mining historical sales to classify them as seasonal, lumpy, slow moving, etc.;
- Choosing the right algorithm based on that classification;
- Then tuning the algorithm parameters to optimize forecast accuracy.

While the statistical forecast is run on daily or weekly basis, the process to choose and tune algorithms is run much less frequently since algorithm choices and even parameters should be stable over the short term.

Advances in Machine Learning, data availability and cognitive computing have enabled a new era. A large number of factors such as social media, news, events, weather, market forces and IoT signals can now be combined to create more intelligent demand forecasts.

JDA has experimented various Machine Learning algorithms:

- Random Forest: ensemble learning from multiple decision trees;
- Support vector regression: it finds a function that deviates by, at most, a given amount from the observation while, at the same time, being as flat as possible;
- Recurrent Neural Networks (RNN): class of neural networks supporting sequences of inputs through internal state representation (memory);
- Probabilistic methods: zero inflated negative binomial distribution.

So far, the most impressive results have been delivered by ensemble methods. Differently from traditional learning methods, the ensemble ones try to build a set of learners, rather than just one, and integrate them.

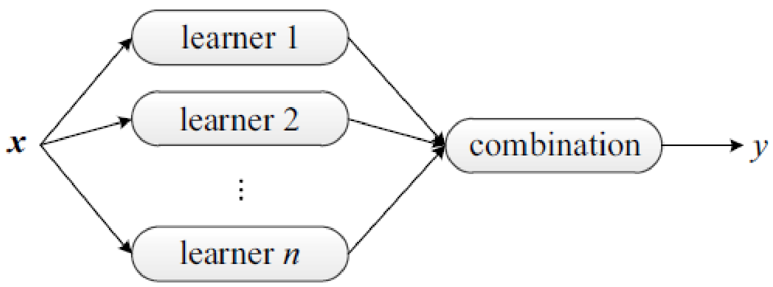


Figure 5-9 Common ensemble architecture

The learners are called “base learners” and are obtained thanks to a base learning algorithm (i.e. neural networks, decision trees, etc.). For the ensemble methods to be effective, it is important to have base learners as diverse as possible. To conclude, these methods allow to use multiple algorithms together to achieve superior predictive performance compared to the one it would be obtained by using any of the algorithms alone, even the best (Zhou 2012).

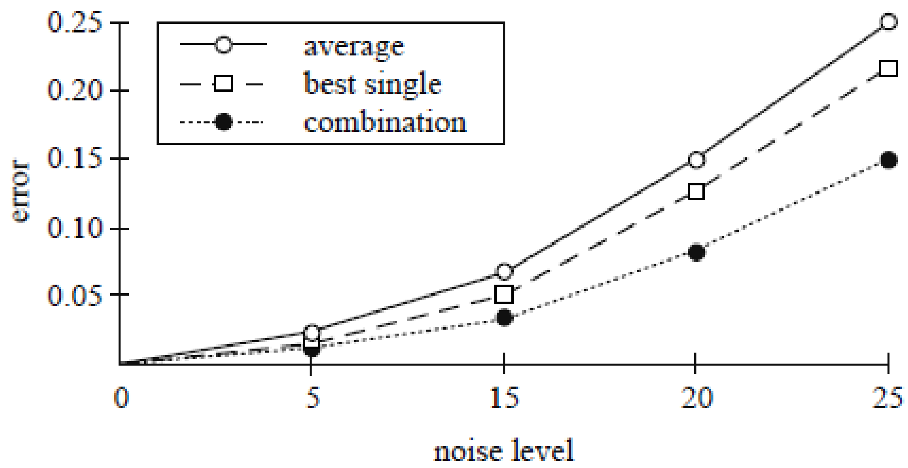


Figure 5-10 Ensemble is often better than the best single

Machine Learning algorithms applied to forecasting lead to higher accuracy but lower explainability. To wrap up, the pros of these algorithms are that they improve forecast accuracy, they provide implicit support for external causal factors and they allow to use one parametrized model for multiple DFUs (Demand Forecasting Unit). While the cons are that it is more difficult to provide explainability, they may be more costly in execution time and memory and less control on model behavior is permitted.

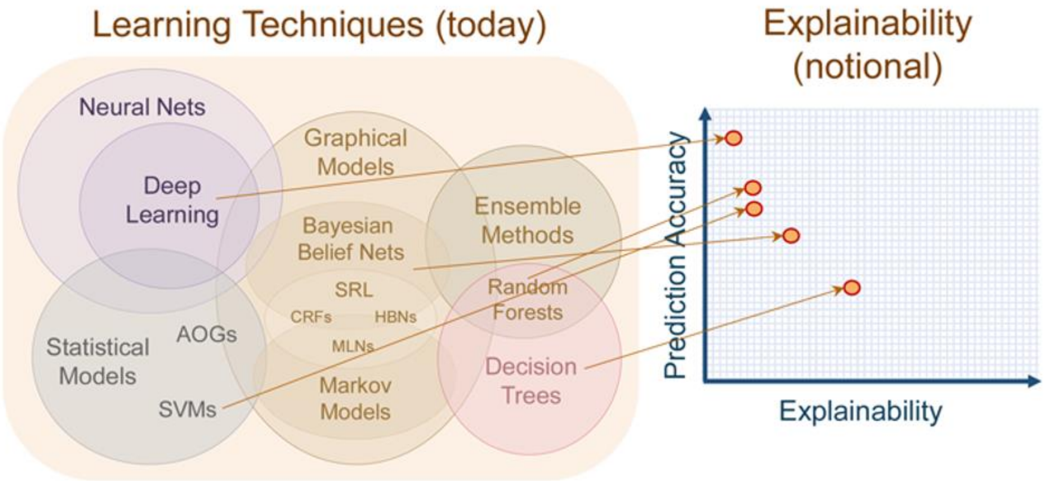


Figure 5-11 Machine Learning - Accuracy vs Explainability

5.3.5 Market Analysis

A big data enabled, digital forecasting solution is applicable to all segments of the market that JDA currently targets. JDA's existing demand forecasting solutions are used by retailers, manufacturers, wholesalers, distributors, 3PLs, hoteliers, airlines, railways and cruise operators. A digital demand management solution has applicability in the above segments.

The primary target markets are retail, manufacturing, distribution and 3PL/4PL. Secondary/opportunistic markets include travel and leisure. PwC puts the addressable market for demand management as a supply chain planning discipline at $1.21B, of which JDA commands about $96M (7% share).

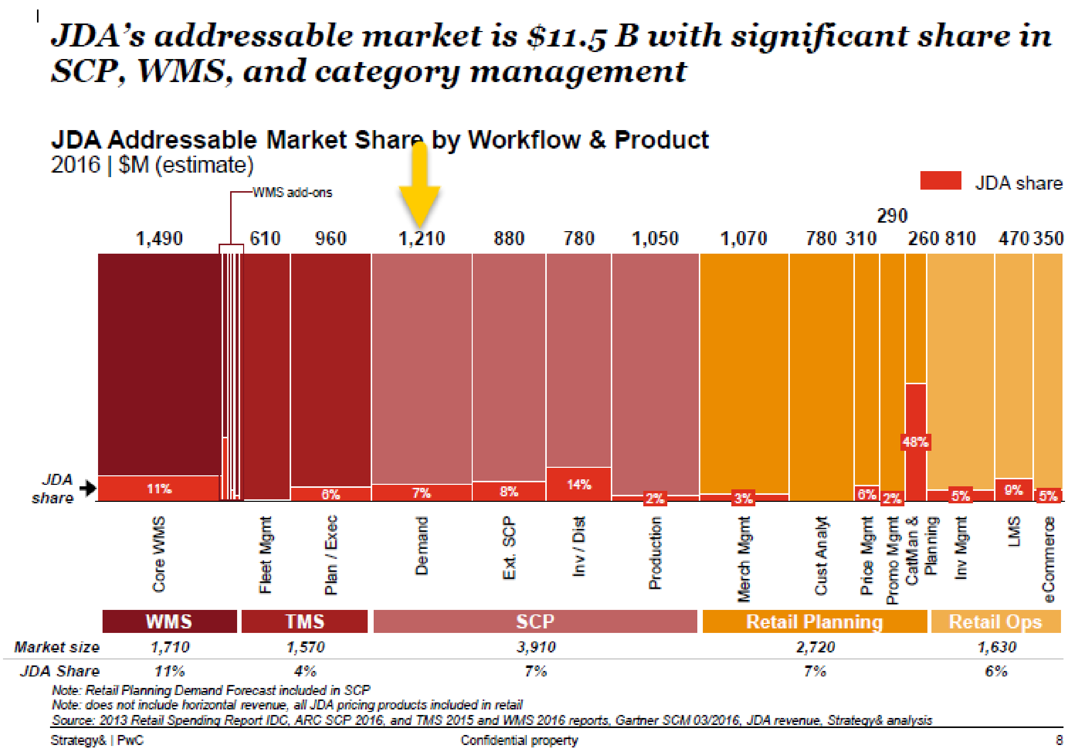


Figure 5-12 JDA addressable market share

Below is a table showing the prioritized market segments and the reasonings for targeting each.

Target Segment	Reasons for Targeting
North America & Europe Grocery & Convenience Retail	North America & Europe are targeted as geographies due to the quantity and quality of external data available. Grocery and convenience experience significant swings in sales due to weather and local events. Furthermore, the relatively short lead times for goods carries in these retailers means higher value in understanding near-term changes in demand.
North America & Europe Hardlines Retail	Like grocery and convenience, hardlines (i.e. hardware/DIY, home goods, toy) retailers are significantly impacted by factors such as weather and local events. They fall behind

Target Segment	Reasons for Targeting
	grocery and convenience in priority because the generally longer lead times impact the value proposition.
North America & Europe Wholesale/Distribution	Companies such as Havi and US Foods experience many of the same challenges as their grocery, convenience and restaurant partners. For companies such as Havi that manage their customers' supply chains, cognitive demand will be a significant value add.
APAC or LATAM Grocery, Convenience, Hardlines	APAC and LATAM are behind North America and Europe in priority because data is more limited and more fragmented in terms of providers. JDA will pursue retailers in these geographies only if they are very strategic to them (i.e. Woolworths Australia) and they have a clear understanding of the use cases and related data availability.
Manufacturing	Many of the use cases for incorporating external signals in manufacturing cover a much longer horizon than in retail. As such, it will take more time to prove the value. Here there are use cases such as housing starts impacting power tools or vehicle sales impacting tire replacements. In both examples, the impact significantly lags the leading indicator. As more manufacturers sell direct to consumers, the demand for new forecasting solutions will quickly grow. It is JDA desire to have a manufacturing success story and they will be opportunistic in choosing the right manufacturer with the right use cases as an early adopter.

5.3.6 Use Cases

Discussing with existing customers and perspective ones, the following use cases have been identified:

- Intra-day planning: increasingly, the trend is to see demand for forecasts in sub-daily buckets and that are refreshed more frequently than an overnight batch.

  As an example, Home Plus, a South Korean grocery spinoff of Tesco, replenishes stores up to three times daily and has shared with JDA that Tesco has a system in place today that enables both forecasting in hourly buckets and updating the forecasting within the day to reflect current trends. This tendency of replenishing stores multiple times per day is increasing in Europe and Asia. Small store formats, densely populated urban areas and relatively short lead times make this an appealing option for maximizing store space while satisfying customers.

  Another example is Woolworths South Africa, it would like to use intra-day forecasts to drive pricing (markdowns) for perishable products. As they see that there will be excess inventory at the end of the day, they want to notify individual stores to reduce prices at strategic times of the day to increase sales (i.e. reducing price just before the dinner hour on prepared foods is far more effective than reducing just after);
- Pace-based forecasting: it is accomplished by borrowing the "booking curve" technique long used in the passenger travel, cargo and hospitality industries. The premise is that by observing historical sales one can deduce

the cumulative percentage of sales that should have occurred at any point in the day. Then, within a day, the forecast for the remainder of the day may be adjusted based on the realized sales and booking curve. This same technique may be applied to improve forecasts within a day, week, month, quarter or season.

Companies such as American Greetings are interested in using the notion of a booking curve to adjust forecasts for highly seasonal products;

- Weather: foot traffic at grocery stores is significantly hampered by heavy rain, conversely, demand for grocery delivery rises sharply with rain, cold weather or snow. Sales forecasts adjusted for current week weather forecasts can impact both labor and inventory spend. Companies such as Woolworths Australia, McDonalds, Walmart and Coca-Cola European Partners have expressed an interest in using near-term weather to improve sales forecasts. Cold weather apparel sales are largely impacted by the severity of winter. When retailers plan for the next season, they often do so using last year as a starting point. If last winter was abnormally warm or cold, the next buy will be too small or too large. By normalizing historical sales to average weather conditions, the long-term buys may be right-sized. Then, in-season allocation decisions may be driven by near-term weather forecasts to ensure inventory is distributed to those markets where it is most likely to sell at full price. Even when pre-season buys are sized appropriately, deployment timing can be a challenge for seasonal products. Consider categories such as lawn care products. The general shape of the seasonal curve may be derived well in advance of the season. However, the first nice day of spring dictates the start of the selling season for those products. An early spring and the entire curve needs to shift forward, a late spring and it needs to shift backwards. By leveraging localized forecasts for the next 1-2 weeks, manufacturers and retailers may position inventory more effectively to capitalize on early sales in the right markets without tying up valuable store space in markets with later breaking spring conditions;

- Local events: an event such as a marathon featuring thousands of runners impacts sales at restaurants, pubs and hotels near the event. Sales at convenience stores for Gatorade, water and snacks increase. By automatically gathering local events and predicting the impact based on similar events in the market, or in similar markets, retailers can increase sales by avoiding product and labor shortages. There is an alternate scenario that couples weather with a local event. Rainy or cold weather on the day of a marathon will also drive demand for ponchos, umbrellas, gloves, warm beverages, etc. for spectators. In this use case, knowing the weather or event insight alone is not enough, but rather the combined effect must be modeled. Companies such as Ahold, Starbucks, Loblaw, McDonalds, 7-Eleven, Walmart and Woolworths Australia have expressed an interest in leveraging local events to improve forecasts.

  Companies like McDonalds would like the ability to use the impact of the London Olympics to forecast sales for McDonalds stores in Rio during the Rio Olympics. They would like this to happen in an automated way accounting for proximity of the store to the events, proximity to athlete housing, etc. There are very similar use cases for the Winter Olympics, World Cup, Super Bowl, various championship and all-star games, tennis tournaments, golf tournaments, major conventions and major shows;

- Social media: companies like Nike, Lego, Coca-Cola European Partners and Starbucks want to leverage unstructured social media (i.e. Facebook, Twitter, Instagram, YouTube etc.) to get an early read on new product performance. By quickly understanding market response, these companies can go more aggressive or back-off marketing. They can reposition inventory and adjust prices to maximize return on assets. Unstructured social media paired with Google search trends can provide companies with early insight into product problems, accelerating resolutions/recalls and minimizing damage to the brand. Structured social media such as Trip Advisor scores or Amazon.com ratings may be used as a leading indicator of future performance. JDA's Trip Advisor-related research has shown that the numeric score itself is not as important as understanding trends in the score.

As with weather, there is value in normalizing sales to remove the noise associated with one-time social media amplifiers. For example, it is now infamous that Red Lobster experienced a 33% increase in sales on Super Bowl Sunday in 2016 after Beyoncé referenced the chain in her new video, which went viral. Red Lobster would not want to mistakenly associate the

33% increase in sales as repeatable Super Bowl or seasonal demand when planning for 2017 and thus normalizing for social anomalies is important;

- Additional external data use cases: companies like Bridgestone, Canadian Tire and Discount Tire have expressed an interest in using vehicle registration records to forecast demand for tires, auto parts and service.

  Starbucks would like early visibility to flight delays and cancellations at major airports. As flight schedules backup and travelers stuck, the traffic into Starbucks airport locations increases significantly. With even a few hours' notice, Starbucks can bring in additional labor to serve the stranded travelers.

  Exxon-Mobile, Bridgestone and Mercedes Benz see an opportunity to leverage vehicle sensors to proactively send demand signals for new parts and vehicle services, enabling positioning of inventory and demand shaping JDA has many customers in spare parts (automotive, machinery, aircraft, military). Forecasting and inventory planning for spare parts is notoriously difficult given the large number of parts and the intermittent and unpredictable failure rates. In-vehicle sensors will increasingly provide advanced signals, creating significant opportunity to rely less on a historical model and more on predictive analytics.

  Companies such as Stanley Black & Decker, Home Depot, Coca-Cola European Partners and PepsiCo and many others want to use competitor price and promotion information to adjust historical sales and future forecasts.

5.3.7 Market Requirements

Customers and prospective customers have provided the use cases and from there the high-level functional requirements to support those use cases have been derived.

Cognition can be broken into three steps: Perception, Intelligence and Learning. The market requirements are organized into these three steps:

1. Perception: first we need to see the world around us. The next generation of demand management processes must perceive the world more holistically and they must do so in real-time or near real-time. JDA solution must close the gap between the physical world and the digital representation.

   We divide the world of demand signals into two high-level categories: internal (enterprise) and external. The internal signals are those pieces of information proprietary to an enterprise, these include attributes such as sales, price, promotion tactics. Enterprise signals may also include those of partners in the network. For a manufacturer, consumer demand from their retail partners is a valuable signal. External signals are those signals which are not unique to the enterprise. Generally speaking, JDA approach is that customers will need to provide JDA with the enterprise data and that JDA should source the external ones.

   - Enterprise data: below is a list of sample enterprise data, visibility to which results in a better demand signal.
     - Sales transactions:
       a. Customer;

b. Product;
c. Requested fulfillment point/method;
d. Actual fulfillment point/method;
e. Order point/method;
f. Price;
g. Any incentives/promotions applied;
h. Any service fees applied.

- Cost of sale;
- Product, location and assortment attributes;
- Clickstreams and path to purchase;
- Loyalty and customer data;
- Inventory;
- Promotional tactics (i.e. displays, ads, digital campaigns);
- Sales plans & targets;
- Assortments, range plans, space plans;
- New product information;
- B2B opportunities;
- IoT devices: they fall under both the enterprise and external data categories. The manufacturer or owner of a given asset may have access to sensors within those assets. This sensor data would be considered enterprise data as it may not be available in the public domain;

- Customer apps: IKEA, as an example, has an app in which customers can design their dream kitchen and ultimately make the purchase. While consumers agonize over the purchase decisions for weeks, the design activity itself is a demand signal.

- External data: below is a list of sample external data, visibility to which results in a better demand signal.
    - Weather;
    - New stories;
    - Social media;
    - Local event calendars & schedules;
    - Traffic conditions;
    - Public holidays;
    - Government assistance distribution schedules;
    - Competitor locations;
    - Sport teams & stars (i.e. performance, scores, win-loss record);
    - Movie reviews/box office sales/show times;
    - Music sales, downloads, plays;
    - Macroeconomic indicators;
    - Ratings & reviews (i.e. Amazon.com, TripAdvisor);
    - Housing starts;
    - Real estate transactions;

- Vehicle registrations;
- Center for Disease Control (CDC) data;
- Commodity prices;
- Census/demographic data;
- Currency exchange rates;
- IoT devices: examples of external IoT signals include traffic sensors, cell phone positions, satellite images.

2. Intelligence: a more timely, holistic view of the world is valuable only if companies are equipped to act in a meaningful way. They must be able to influence a key business metric with the new information available.

   Within the demand management domain, there are three high level categories of use cases that emerge in terms of taking an intelligent action:

   - Explain prior performance: demand management practitioners and their stakeholders in the organization are constantly challenged to explain changes in selling patterns. The challenge today is that because organizations are blind to many of the factors driving demand at a local level, this process is incredibly manual, typically resides outside of systems and is heavily dependent upon tribal knowledge. JDA customers seek visibility to the layers of demand so that they can articulate why demand is what it is;
   - Forecast future demand: below there are the primary use cases for a demand forecast in JDA's current markets. For the Cognitive Demand initiative, the inventory planning use cases are the priority

as this is where JDA Demand is most often used today and thus offers a fast path to customer adoption.

- Inventory planning: the process of determining how much inventory to purchase and where to hold it is heavily dependent upon a forecast. In the past, retailers generally used forecasts at a SKU/Store/Week level to make inventory decisions while manufacturers and distributors typically used forecasts at a SKU/DC/Week or Month level. The emergence of omni-channel buying now means that while companies were happy with weekly forecasts in the past, the demand in some industries is now for hourly forecasts. The next-generation of demand management systems must account for channel and must have the ability to be as granular as hours in the time dimension;
- Labor planning: determining how much and what type of labor should be available in a store or a distribution center relies upon a forecast. However, unlike inventory, these forecasts are not necessarily based upon sales of products. In a distribution center, labor requirements are derived by understanding the inbound and outbound workload. How many trucks will need to be loaded or unloaded during this shift? Are they pallets or slip sheets? How many orders need to be picked? Etc. In stores, the labor plan is equally

complex. The number of customers expected to enter the store (foot traffic), the number of items purchased, the quantity of returns are all factors. Labor plans often must be as detailed as 15-minute increments;

    - Financial planning: it requires a sales forecast as in important input. The desire is typically that the demand forecast feeding the financial plan be constrained by known limitations such as product availability, labor constraints, physical space, etc. These plans are typically not nearly as granular as inventory plans in terms of product, location or time. However, the expectations for precision are much higher because of the less granular nature;
    - Strategic planning: long-term strategic plans are driven by a sales forecast. Like financial plans, these forecasts are typically at a very high-level aggregation.

- Shape future demand: once organizations have a good picture of current market demand, they can employ tactics to shape demand to accomplish the company's financial goals. Demand shaping activities require many of the same models as demand forecasting, thus these initiatives are closely linked. Below are demand shaping processes that typically require demand modeling.
    - Assortment planning: assortment plans are driven by estimates of what consumers will purchase. Forecasts used

in assortment planning processes must consider the transferability of demand to properly understand the incremental sales of any specific item to be added or deleted. In addition to transferability, the notion of leveraging attributes to create a sales forecast is important to this process. Many items involved in the assortment decisions have never been carried in the past and thus sales estimates must be derived from similar items;

- Space planning: when allocating space within a store to product families (macro space) or space within a fixture to items (micro space), an understanding of demand is important. Higher selling products should be placed in premium locations while slower moving products receive less desirable locations. The notion of 'space elasticity' may be used to determine the magnitude of sales growth achievable by increasing physical presence. Lastly, consumer segmentation plays a role. Place the children's cereal on the top shelf where they cannot see or reach it and sales will almost suffer as compared to the item at their eye level. Space decisions are typically made infrequently so demand forecasts can often be in monthly or quarterly buckets. However, because every store is a bit different, the best space plans are those that understand the nuances of the specific store;

  - Price & promotion: these plans are often seeded with the sales forecast, compared against the financial plans and then campaigns are planned to bring the sales forecast in line with the financial plan. These processes require the ability to model price elasticity as well as the impact of non-price demand drivers such as advertising, premium positioning in stores, featured locations on the website, etc. Competitor activity is often a major consideration in these processes and may impact the demand forecast significantly. Lastly, halo and cannibalization are major factors in these decisions and thus must be included as factors in the demand models.

3. Learning: after perceiving the world in a more timely, holistic manner and subsequently acting to improve business results, we must be able to learn from the actions and outcomes. Below are sample use cases for a demand management system that learns over time.

   - Score input signals: a self-learning system may deduce after some period of time that the weather forecast, for example, in a particular geography is so inaccurate or volatile that it provides no predictive value and thus choose to remove that signal from very specific locations;

- Find new signals: a self-learning system can look for additional signals, not currently included in the model and recommend their inclusion;
- Prescriptive resolution levers: the market demands systems based on a “manage by exception” paradigm. In this paradigm, users are alerted to potential problems and asked to take actions. A self-learning system will observe these actions over time and eventually move from simply asking them to take an action to recommending one or more actions based on things they or their peers may have done in the past. In time, the system may move from recommending a resolution to directly taking an action and merely notifying a user.

5.3.8 Competitors Analysis

The demand planning solution market is a crowded one with no single player controlling a dominant position. JDA is viewed as a leader in this space as demonstrated by the position in Gartner’s magic quadrant. Looking at the changing competitive landscape associated with big data, edge-connected demand planning, it is possible to break vendors down into three broad categories:

1. Big data forecasting: these are providers that can derive multi-variant causal forecasts but they do so primarily in isolation. These companies have limited or no supply chain or retail planning assets. Their customers must undertake an effort to integrate this demand signal into their

planning ecosystem in a meaningful way. Solution providers in this category include IBM, Prevedere and SAS Institute;

2. Big data forecasting with retail or supply chain solution ecosystem: like the category above, these companies can deliver multi-variant causal forecasts. They also have broader supply chain or retail planning solutions that derive value from the forecast. Companies in this category include Blue Yonder, Relex, Oracle, Infor and E2Open;
3. Machine learning big data forecasting with significant retail and supply chain solution ecosystem: these providers are set apart from the above two categories based on their unique combination of end-to-end supply chain and retail planning with leading-edge machine learning techniques. These companies can most quickly integrate the improved demand signal into the enterprise given the broad solution footprint. At the same time, they can offer a top-quality answer. JDA and SAP appear to be the strongest candidates to dominate this category.

Below is a table showing the existing direct and indirect competitors.

N. America		**Europe**		**Asia**	
Direct	Indirect	Direct	Indirect	Direct	Indirect
Blue Yonder	Prevedere	Blue Yonder	Prevedere		
Relex		Relex			
IBM		IBM		IBM	
SAS		SAS		SAS	

Predictix (Infor)		Predictix (Infor)		Predictix (Infor)	
Oracle		Oracle		Oracle	
E2Open		E2Open		E2Open	
SAP		SAP		SAP	

As the table shows, Blue Yonder was JDA main competitor in this market. The recent acquisition has transformed Blue Yonder from a rival to an important resource that will provide a significant advantage over competitors.

Below is the Gartner 2015 Magic Quadrant for Supply Chain Planning System of Record. JDA's point-of-differentiation against companies like IBM, INFOR, Oracle, etc. should be that JDA brings the full supply chain solution to bare. An improved demand forecast delivers no value to an organization unless it may be leveraged to improve customer satisfaction or increase asset utilization. JDA is well-positioned to combine Cognitive Demand management with its existing supply chain solutions to deliver results in an orchestrated workflow.

Figure 5-13 Magic quadrant for Supply Chain Planning System of Record

5.3.9 Results from the PoC

The two PoC that are going on show encouraging results.

The first one is a famous Canadian supermarket chain. The main objective for them was to reduce the WMAPE (Weighted Mean Absolute Percentage Error). Particularly, the target was a 10 points reduction. By using RNN as algorithm, they achieved the goal and they actually performed even better. As we can see from Fig. 5-14, the WMAPE decreased from 52.3 to 39.9 for bread and from 57.9 to 37.8 for yogurt, furthermore there was a strong reduction in the bias as well. The major improvements were in fast movers, which is positive since they were the most important products for the company.

		RNN			Company 1 Total		
		Win	WMAPE (%)	BIAS(%)	Win	WMAPE (%)	BIAS(%)
Bread		**17754**	**39.9**	**5.3**	**3588**	**52.3**	**14**
	Fast movers	6878	19.1	-1.4	391	35.8	13.9
	Slow movers	2370	70.5	18.1	605	93.1	11.6
	Others	8506	39.6	6.2	2592	52.2	14.7
Yogurt		**52519**	**37.8**	**8.9**	**5849**	**57.9**	**-1.2**
	Fast movers	5914	25.3	1.4	212	43.8	0.6
	Slow movers	5332	55.3	20.6	962	78.5	11.6
	Others	41273	37.1	8.2	4675	57.0	-3.2
Total Win		**70273**			**9437**		
	Percentage Win	**88.2%**			**11.8%**		

Figure 5-14 PoC results - Canadian supermarket

The second one is a renowned British multinational company specialized in retail sales. In this case, forecast results are satisfactory at the stroke color level for store (lag 0). The RNN at the stroke color and daily level improves the accuracy for lag 0 by about 62% and bias by 66%, as shown in Fig. 5-15.

Lag 0 Algorithm	Win	WMAPE (%)	WBIAS (%)
RNN	90%	44.2	0.39
Forecast	10%	106.9	-67.3
Delta		62.7	
# DFU = 1,613			

Figure 5-15 PoC results - Forecast with weather and promo at the daily level and stroke colors product level

JDA ML forecasts also achieved 80% forecast accuracy at the item/restaurant/day level for a UK-based restaurant chain.

5.3.10 What Changes After BlueYonder Acquisition

This research was carried on before BlueYonder (BY) acquisition. At the beginning of November, I had the chance to visit BY headquarter in Karlsruhe, Germany, and understand more about their solutions and how JDA will leverage their knowledge and capabilities.

BY is focused just on Retail and it has two solutions: Replenishment Optimization and Price Optimization. The one that is going to augment Cognitive Demand JDA solution is Replenishment Optimization. Its goal is to optimize the supply chain, "What do I need to order and where?" is the main question it solves for. Customer demand is what drives everything, so there is a bottom-up approach (starting from customer demand and going up to the entire supply chain). It allows to consider more than 200 demand factors, such as:

- Sales;
- Day of the week;
- Seasonality;
- Day of the month (payday as an example);
- Stock availability: it is necessary to have daily stock availability, while historical one is not mandatory, but its absence will cause a lower performance;
- Listings;
- Location parameters;
- Price: it is important for a customer to provide historical price;
- Product parameters;

- Cannibalization: this factor is easy to understand when products belong to the same group, while it is hard when they fall into two different product groups (e.g. fresh chicken meat vs fresh beef meat);
- Promotions;
- Relations: there are moments in which a company has both the old and the new products, it can sell both but it can order just the new one. This is usually a factor difficult to provide;
- Weather forecast: this factor does not need to be provided by the customer, it is automatically included by BY;
- Holidays.

These factors can be linked (e.g. 30 degrees on Sunday will probably determine a higher number of barbecue and, consequently, more meat will be sold. While 30 degrees on Wednesday will probably have a smaller impact). The link is automatically generated thanks to ML, but BY provides data to the algorithm in a way that facilitates it.

BY solution is not using traditional ML algorithms, but they have a proprietary one called Cyclic Boosting. One of its strengths is that it is able to show the influence of the single factor, this means that the explainability is higher compared to the other ML algorithms. Replenishment Optimizations follows two main steps:

1. The first step is the forecast. This forecast has a high quality since it is done at the most granular level, meaning for each product, location and day (it is not calculated on the whole week and then de-aggregated by standard percentages, as it is common in traditional forecasting), it is updated every

day and the horizon is 21 days. Another fundamental feature of this solution is the output, which is represented not as a mean value, but as a probability distribution;

2. The second step is represented by the replenishment process. There can be reasons for ordering more (such as to avoid stockout), but also reasons for ordering less (such as to avoid waste and to decrease inventory levels). Based on the strategy chosen by the customer (e.g. reduce lost sales, reduce waste, reduce inventories, reduce cost-to-serve, etc.), on the constraints (e.g. pack quantity, min/max order quantities, shelf capacity, current stock level, shelf life, etc.) and on the probability distribution, an optimization function allows the company to order the right quantity, at the right time and in the right place.

An example of use case can be the quantity of meat that has to be ordered by two different stores (of the same brand) with different weather forecasts. By knowing the strategy (higher priority on availability), the price, the day of the week (Friday), the constraints (pack quantity equal to 4, shelf life equal to 3 days and lead time equal to 1 day) and the two different weather forecasts (20°C and sunny for a store, while 30°C and 50% probability of rain for the other), Fig. 5-16 shows the probability distributions that are obtained and thanks to which it is possible to calculate both the risk of stockout and the risk of waste.

Fig. 5-17 shows that, even if the forecast mean is the same (equal to 15), the quantity to be ordered is 24 for the first store and 32 for the second one.

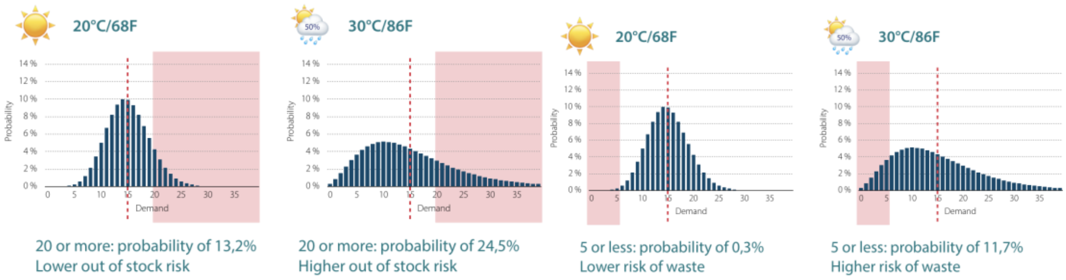


Figure 5-16 Different Probability Distributions

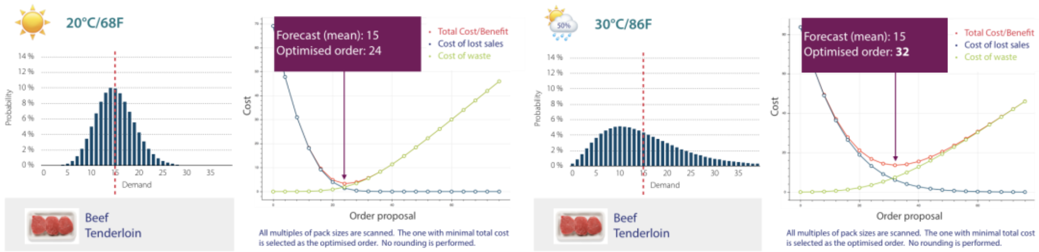


Figure 5-17 Different Order Decisions

Taking into considerations BY solution, some changes to the S.W.O.T. Analysis presented before need to be done. For what concerns the strengths:

- BY solution allows to reach 99% of automation (and not 90%);
- JDA estimates can be replaced by "real" numbers obtained with BY customers. At Morrisons, BY solution achieved 2-3 days reduction in stock holding in-stores and 30% shelf gap reduction. At Otto, it increased profits and revenues by 6-12%;
- A new point of strength is represented by the fact that BY is extremely fast in training the algorithm.

About the weaknesses, most of them turn into strengths by using BY solution:

- It works well also with NPI;
- BY perfectly knows the data the algorithm needs, so the data collection problem is solved;
- It is possible to identify the connection between data and effect on sale;
- The combined effect of two or more external factors is analyzed;
- Data quality checking process is not fully automatized, but BY has a standard and robust model for data quality checking that helps;

- The new weakness is “effort VS value”, meaning that some companies can be interested in the solution but the business case is not big enough.

5.4 Cognitive Demand Readiness Assessment

The deliverable of this internship was also the creation of a Readiness Assessment in the form of questionnaire. The objective of this assessment is to test if a company is qualified to implement JDA Cognitive Demand solution.

The first step is to define the different maturity levels in the demand planning process and to which level a company should belong in order to be considered “ready”.

The second step consists in the development of a set of questions, each one with a predefined weight, and the identification of a scoring method that will influence the final risk scoring.

The third and last step is to choose how to display the results of the assessment and come up with a proposed mitigation plan.

All these steps will be examined in depth in the next paragraphs.

5.4.1 Literature Review

A limited number of digital maturity models can be found in the literature. There are three main types of maturity models: maturity grids, Likert-like questionnaires and CMM-like models. The first type describes maturity levels in a grid structure. Likert-like questionnaires are based on a set of questions and the available answers are on a scale from 1 to n. There can be also hybrid models that mix the characteristics and features of both maturity grids and Likert-like questionnaires.

The most widely used is the third type of maturity model, the CMMI (Capability Maturity Model Integration) and it has served as a basis for mostly all the other models developed afterwards. It is made of five levels, each of them defining the capabilities a company belonging to that specific level has (CMMI). The limitation of this model is that it is too detailed and it requires large expenditures for its full implementation.

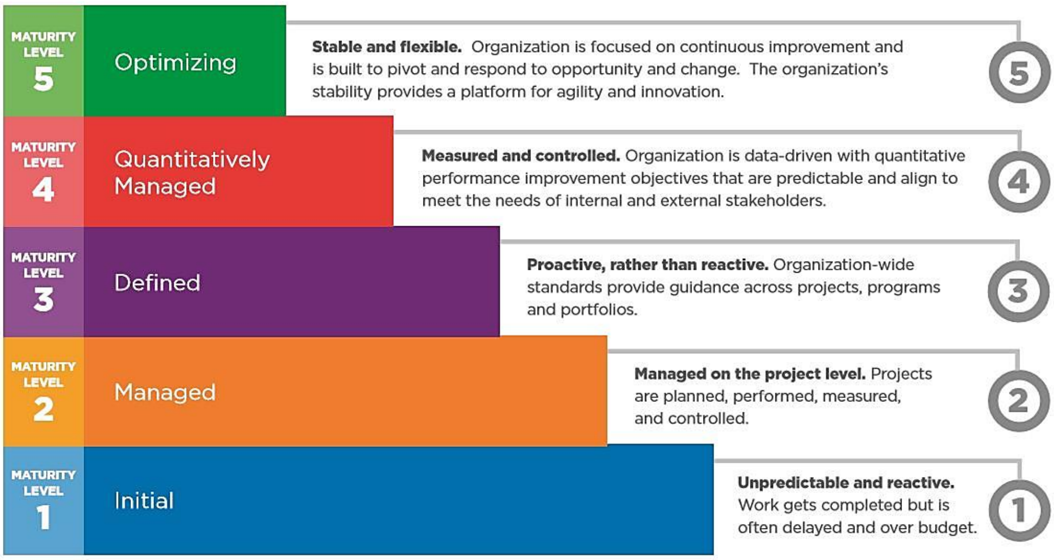


Figure 5-18 CMMI five-scale maturity levels

Based on the CMMI, some professors from Politecnico di Milano developed a new model called “DREAMY” (Digital REadiness Assessment MaturitY model). First, they identified five areas in which manufacturing company’s processes can be grouped:

1. Design and Engineering;

2. Production Management;
3. Quality Management;
4. Maintenance Management;
5. Logistics Management.

They decided to elaborate the analysis on four dimensions, including not just process and technology, but also the organizational point of view:

1. Process;
2. Monitoring and Control;
3. Technology;
4. Organization.

At this point, they established and described the five maturity levels shown below.

Maturity level	Description
ML1 INITIAL	The process is poorly controlled or not controlled at all, process management is reactive and does not have the proper organizational and technological "tools" for building an infrastructure that will allow repeatability /usability /extensibility of the utilized solutions
ML2 MANAGED	The process is partially planned and implemented. Process management is weak due to lacks in the organization and/or enabling technologies. The choices are driven by specific objectives of single projects of integration and/or by the experience of the planner, which demonstrates a partial maturity in managing the infrastructure development
ML3 DEFINED	The process is defined thanks to the planning and the implementation of good practices and management procedures. The management of the process is limited by some constraints on the organizational responsibilities and /or on the enabling technologies. Therefore, the planning and the implementation of the process highlights some gaps/ lacks of integration and interoperability in the applications and in the information exchange
ML4 INTEGRATED AND INTEROPERABLE	Being the process built on the integration and on the interoperability of some applications and on the information exchange, it is fully planned and implemented. The integration and the interoperability are based on common and shared standards within the company, borrowed from intra- and/or cross-industry de facto standard, with respect to the best practices in industry in both the spheres of the organization and enabling technologies
ML5 DIGITAL-ORIENTED	The process is digital oriented and is based on a solid technology infrastructure and on a high potential growth organization, which supports – through high level of integration and interoperability – speed, robustness and security in information exchange, in collaboration among the company functions and in the decision making

Figure 5-19 DREAMY Maturity Levels

They populated the maturity model by realizing a Digital Readiness Questionnaire. For each question they defined, thanks to field experts and academic material, five possible answers corresponding to an increasing maturity level (De Carolis 2017).

The picture below graphically represents the structure of this model, the "Backbone" indicates the software tools allowing the connection and exchange of information among all the areas (De Carolis 2017).

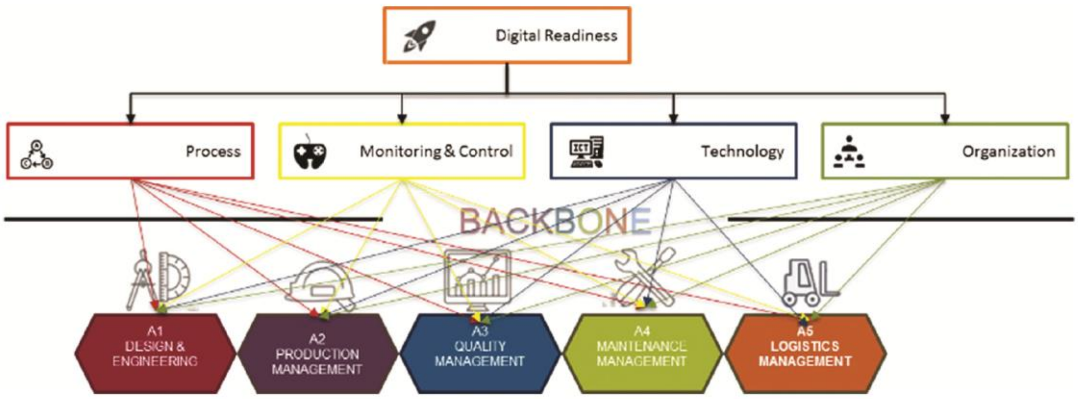


Figure 5-20 DREAMY Model structure

The DREAMY can be compared with the SMSRL and MOM models. SMSRL (Smart Manufacturing Readiness Level) is an index that defines the readiness of a manufacturing company for implementing smart manufacturing principles. It is based on the factory design and improvement (FDI) processes. The structure is shown below.

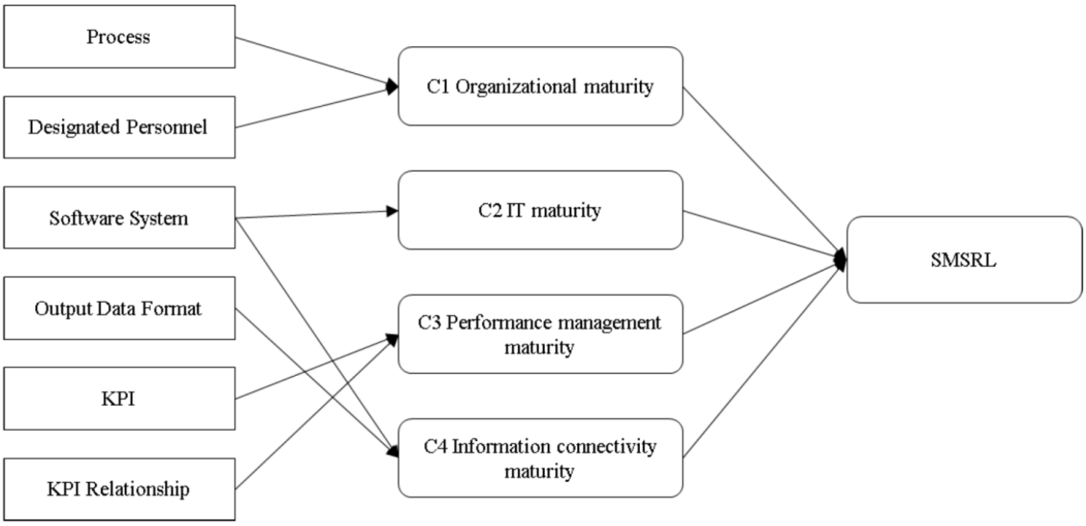


Figure 5-21 SMSRL structure

The MOM (Manufacturing Operations Management) Maturity Model measures the maturity of manufacturing facilities. It covers four areas: Production Operations Management, Inventory Management, Quality Test Operations Management, Maintenance Operations Management. Each area involves different activities: Scheduling, Dispatching, Execution Management, Resource Management, Definition Management, Data Collection, Tracking and Performance Analysis. For each activity the maturity can go from 0 to 5, as shown in the table below.

Level 0	There has been no evaluation performed.
Level 1	Procedures for activities and their executions are at initial stage and not documented or formally managed.
Level 2	Procedures of some activities are documented and executed with possibly repeatable results in the normal situation.
Level 3	Procedures for activities are defined with documented standards for all activities whose executions are possibly supported by software tools and better handling of abnormal situations.
Level 4	Procedures for activities are defined and documented across all organizational groups; and their executions are repeatable and monitored with software tools supports.
Level 5	Procedures for activities are focused on continuous improvement and optimization.

Figure 5-22 MOM maturity levels

This model has 832 questions, thus becoming time consuming and it also lacks proposed improvement strategies after the results are analyzed.

The table below compares the three models: DREAMY, SMSRL and MOM (De Carolis 2011).

Element	DREAMY	SMSRL	MOM
Objective(s)	1. To assess a manufacturing company readiness level for starting the digital transformation process 2. To identify strengths and weaknesses and related opportunities manufacturers can gather from the digital transformation, with the final aim to help them in defining a roadmap for prioritizing investments	To assess a manufacturing company's readiness to employ data-intensive technologies for its performance management.	To determine level of an organization's capability to have mature, robust, and repeatable manufacturing operations [24].
Focus	Manufacturing company / Product and Factory Life Cycles	Maturity of performance improvement tasks/processes, availability of software supports, maturity of information sharing capability, and availability of responsible personnel	Manufacturing Operations Management (MOM) processes
Analysis Dimensions	Process / Execution, Monitoring and control, Organization, Technology	Organization, IT, Performance Management (process execution), and Information Connectivity	Process / Execution
Process Areas	Product and asset design and engineering, Production management, Quality management, Maintenance management, Logistics management, Digital Backbone	(Change) Requirement developments, Basic (rough) design of a new or a change requirement, Detail design, and Test	Production Operations Management, Inventory Management, Quality Test Operations Management, Maintenance Operations Management
Maturity levels	5 (1-5)	6 (0-5)	6 (0-5)
Inspiring framework	CMMI	Factory Design and Improvement Activity model	ISA-95 Enterprise Control Activities
Assessment methods	Interview / case study	Self-assessment	Self-assessment
Model purpose	Descriptive and prescriptive	Descriptive and comparative	Descriptive and comparative
Questions / Answers' type	Questions with normative answers	Yes/No Question, Scoring Question	Yes/No Questions
Number of questions	About 200 scoring questions	242 scoring and at least ~123 Yes/No questions	832 Yes/No Questions

Figure 5-23 Comparison among DREAMY, SMSRL and MOM models

Another input to my work is represented by Hai Zhu's Master Thesis. He developed the SIMM (Smart Industry Maturity Model) starting from both the CMMI and Porter's value chain model as a base. This model is made of the following parts:

1. SIMM elements and relevant technologies and methods (TMs);
2. KPIs and Market Trends;
3. SIMM processes and relevant Value-add points (VAPs);
4. SIMM maturity levels and relevant questionnaire.

To develop his study, he applied the Design Research Methodology that consists of four stages, illustrated in Fig, 5-24.

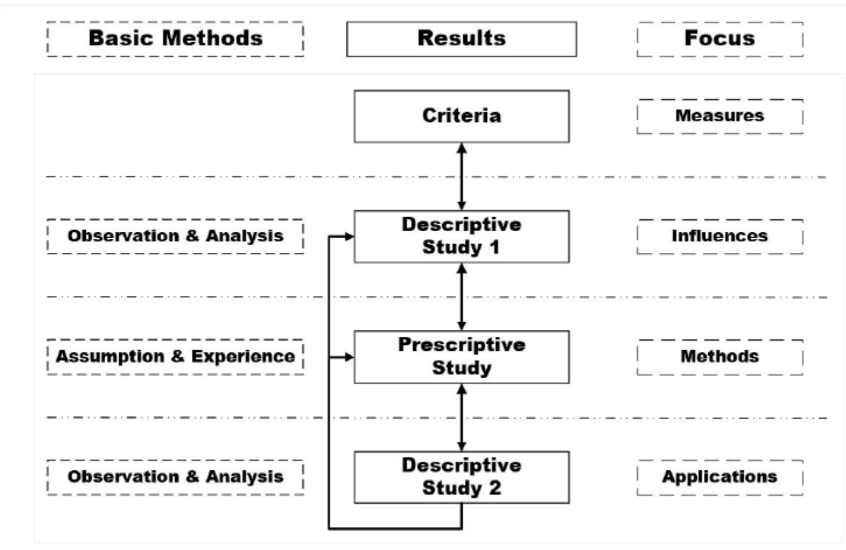


Figure 5-24 Design Research Methodology

1. Criteria: in this phase the context, the questions to be solved and the scope are identified;
2. Descriptive Study 1: it consists of the literature consultation;

3. Prescriptive Study: based on the findings of the previous step, a new model is elaborated;
4. Descriptive Study 2: it is the evaluation of the model just created.

Referring to the first part of the model, there are twenty-four TMs and the SIMM elements are seven:

1. Prosumer & Mass customization;
2. Co-creation & Smart product development;
3. Cyber physical system & Factory flexibility;
4. Internet of Things & Digital factory;
5. Enterprise agility & Competent workforce;
6. Operational excellence & Variation reduction;
7. Eco-production & Made different.

According to Zhu, it is important to understand the areas in which digitalization and new technologies can be used to lead companies towards the achievement of their objectives. For this reason, he identified eight business processes and several VAPs. For what concerns KPIs, the six selected are:

1. Productivity;
2. Time to market;
3. Market share;
4. Resilience;
5. Revenue;
6. Cost.

The picture below shows the structure of the SIMM and how the four different parts of the model interact with each other.

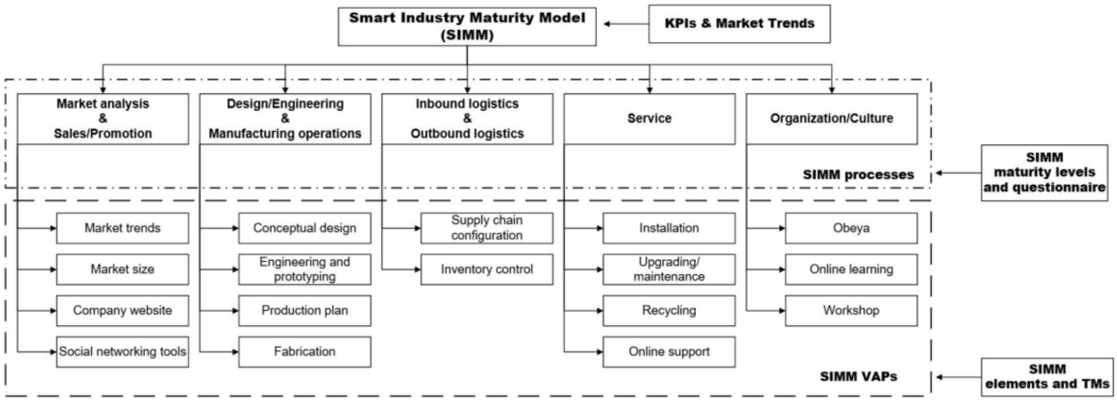


Figure 5-25 SIMM structure

At this point, the SIMM maturity levels are developed, and they are:

1. Initial: companies are not informed about the new trends;
2. Aware: companies are now aware of Smart Industry trends, but they are not able to implement it;
3. Visible: companies have achieved a partial implementation;
4. Improvable: companies have a complete understanding of the interaction among the different parts of the SIMM and this allow them to take decisions faster;
5. Optimized: companies are able to improve their KPIs thanks to the full implementation of the Smart Industry approach.

As for the DREAMY, also in this model there are five possible pre-defined answers to each question. The first, the third and the fifth answers correspond respectively to the lowest, the medium and the highest levels of maturity. Through a weight and scoring mechanism, the maturity score is computed and the SIMM maturity level is identified. This model was tested in three companies: company A operating in the health care sector, company B providing services and products for electric power and company C involved in the business of sustainable energy. The results obtained proved the robustness of the model and all the three companies agreed on the validity and usefulness of the tool (Zhu 2017).

Gartner developed a maturity model specific for Demand Planning which is defined by them as “the development of a consensus-driven demand plan that optimizes the balance between market opportunity and supply network capability”. A Gartner research conducted on 417 manufacturing companies showed a strong correlation between Demand Planning process improvement and performance (Pukkila 2017).

The maturity model is made of five levels (described in detail in Fig. 5-26):

1. React;
2. Anticipate;
3. Integrate;
4. Collaborate;
5. Orchestrate.

Their research shows that most companies are at stage 1 or stage 2. For each level of maturity, they focused on five dimensions (Salley 2016):

1. Objective: the alignment between the objectives of Demand Planning and the ones of the entire supply chain;
2. Process: the activities performed by Demand Planning that become clearer and more standardized as the level of maturity increases;

3. Organization: it indicates the role of the supply chain in the Demand Planning process;
4. Performance Management: the definition of KPIs to measure the effectiveness of the Demand Planning process;
5. Technology: the use of technology platforms and software tools that allow an improved Demand Planning.

Dimensions	Stage 1: React	Stage 2: Anticipate	Stage 3: Integrate	Stage 4: Collaborate	Stage 5: Orchestrate
Objective	Sales-based forecast using historical data	Forecast using data from internal sources	Internally based consensus demand plan	Value-chain-based collaborative demand plan with internal and external stakeholders	Network-based demand plan, expanding the sphere of influence beyond immediate supply chain partners
Process	Development of a baseline forecast using historical sales	Development of a forecast incorporating internal inputs	Development of a demand plan, including internal inputs	Development of a demand plan, including external partner inputs, along with appropriate scenario planning and risk assessment	Development of a demand plan based on the creation of new demand channels that consider social and environmental factors
Organization	Decentralized, with forecast level aligned with sales forecast level	BU or regional planning focused on more granular forecasting	Centralized planning group fills in gaps between interdepartmental plan numbers	Planning group fills in gaps between internal and external partner plan numbers	Planning group supports the commercial organization's identification of new demand streams and segments
Performance Management	Metrics used to identify what happened in previous month/ quarter	Objective is to measure health and effectiveness of process	Objective is to identify value-add of activities and data	Objective is to co-own metrics with collaboration partners working toward achieving joint business goals	Objective is to co-own metrics with network partners
Technology	Technology used to aid planners in refining forecast	Technology used to include inputs from multiple sources	Technology used to enable internal collaboration	Technology used to enable external collaboration	Technology used to enable network relationship management

Figure 5-26 Gartner Demand Planning maturity levels

The result of this assessment leads to the identification of the gaps between the actual-state and the desired one and establishes a roadmap to fill these gaps. In fact, a set of recommendations for moving from a level to the one after is provided. It is in the form of a timeline and it specifies the high/medium/low priority objectives for each dimension (Pukkila 2017). In my opinion, Gartner maturity model lacks an in-depth analysis of both people and change dimensions.

5.4.2 Demand Planning Maturity Levels

A certain level of capabilities is required to be able to successfully implement JDA Cognitive Demand solution. This is the reason why the identification of different Demand Planning maturity levels is needed. Thanks both to the literature and to the discussions I had with field experts, I developed a four stages maturity model for the Demand Planning process.

I focused on four areas and several sub-areas, called respectively "Perspectives" and "Radials":

1. People
    a. Sponsorship: the degree of involvement and support from the executive-level;
    b. Organizational Design: how roles and accountability for Demand Planning process are defined and the level of collaboration with external partners;
    c. Focus & Objective: the needs Demand Planning process solves for and the focus of the company;

    d. Culture: how much a company is “open-mind”. Meaning the degree of openness towards innovation, change and new technologies and the importance given to Demand Planning.
2. Process
    a. Planning Horizon: the length of the planning horizon;
    b. Process Documentation: the level of standardization and accessibility of the documentation concerning the Demand Planning process;
    c. Product & Portfolio: how the forecast incorporates new products and services and at which stage;
    d. Demand: how forecast incorporates insights coming from different functions, as well as forecast value-add thinking and cognitive external signals;
    e. Supply: being able to have a more accurate forecast makes no difference if the supply side is not reactive enough;
    f. Project Management: an agile methodology is required for implementing Cognitive Demand;
    g. Executive Decision Making: the level of effectiveness of the decision-making process.
3. Technology
    a. Data: the importance of data quality and of having a central repository from where data can be easily accessed;

b. Solutions: the tools used for Demand Planning, starting from spreadsheets in level 1 up to Machine Learning solutions in level 4;
c. Reports: the level of standardization of reports;
d. KPIs: which KPIs are calculated and how results are analyzed;
e. Analytics: an increasing level of maturity is associated based on the type of analytics a company performs (descriptive, predictive and prescriptive);
f. Cognitive Insights: how cognitive insights (social media, news, events, weather, etc.) are embedded in the Demand Planning process.

4. Change
    a. Change Effectiveness: how change effectiveness is tracked and monitored, through which instruments and with which frequency;
    b. Communications: communication channels used and the presence of a formal communication plan;
    c. Scaffold Learning: how the training for the Demand Planning solution is conducted;
    d. Continuous Improvement: how frequently Demand Planning maturity is assessed and how continuous improvement is assured.

Many maturity models lack an in-depth analysis of both people and change dimensions which are, in my opinion, the fundamental ones. People are the “engine” that powers the transformation, and just by infusing the right culture within the company and by effectively managing change, a company can leverage its processes and technologies to achieve its goal.

The four maturity levels are (the detailed description can be seen at the end of this chapter in Attachments 1,2):

1. Firefighting;
2. Co-ordinating;
3. Integrating;
4. Synchronizing.

5.4.3 Readiness Assessment Questionnaire

Having defined the maturity levels, I identified a set of questions for each perspective and radial, with three possible answers: Yes, To some extent, Not at all. In total there are 85 questions and each of them has a specific weight (chosen on a scale from 1 to 5).

For "People" perspective, the questions are:

- Are roles and responsibilities for Demand Planning clearly defined?
- Does Supply Chain coordinate/own the Demand Planning process?
- Are there formal Demand Planning roles and job titles?
- Is the demand planner a dedicated role?
- Is there a formal career path?
- Is there awareness of the skills needed to successfully embrace digitalization and Cognitive Demand?

- Is there any involvement from Executive level in the Demand Planning process?
- Are external partners included in the process?
- Are the objectives of Demand Planning defined and clear?
- Does the focus of Demand Planning go beyond the fulfillment of immediate demand?
- Are internal insights and external inputs taken into consideration?
- Does the forecast allow to reach an appropriate level of granularity?
- Are customer demand segmentation frameworks and approaches developed?
- Are risks and what-if scenarios evaluated?
- Is the objective to identify strategies for sustainable business growth?
- Does the Demand Planning process provide at-a-glance figures, supported by clear assumptions and identified issues for the management team's decision-making process?
- Is Demand Planning part of your corporate strategy?
- Do you think the Sales Team understands the impact of Demand Planning on the company's ability to satisfy the customer?
- Do you think all Demand Planning participants understand the wider Demand Planning process beyond their area of participation?
- Do you think there is a culture built on trust and open to innovation within your company?
- Is your company interested in cutting-edge technologies?

- Do you think the benefits deriving from collaboration in Demand Planning meetings are understood and accepted by Marketing, Sales, Operations and Finance?
- Do you think the Demand Planning process is fully embedded in the culture of your business?

For “Process” perspective, the questions are:

- Does your planning horizon allow you to have a medium/long term view?
- Do all regions and markets that participate in your Demand Planning process provide forecasts that cover the agreed planning horizon?
- Does your planning horizon allow you to monitor delivery of the strategic plan rather than just the annual plan?
- Does each process step have clearly defined standard reports?
- Is there an up-to-date Demand Planning process flow map showing key processes and meetings?
- Is the Demand Planning policy fully documented? On participants, responsibilities, timing and objectives for each step?
- Is the Demand Planning documentation accessible in a central repository for all process participants (e.g. SharePoint, Intranet, OneDrive)?
- Is a clear picture provided, in which assumptions, risks and opportunities are understood, before giving direction and making decisions?

- Does the business have a clear picture of all the projects underway in the business and their impact on the business forecast?
- As NPI products move through the stage and gate process, are forecasts regularly updated?
- Does the business review the SKUs portfolio every month managing phase-ins and phase-outs in a controlled manner?
- Is the Demand Planning process based on historical data together with insights provided by different functions (e.g. Statistics, Sales, Marketing, Finance)?
- Is consensus reached by functions on the forecast?
- Is the company willing to include externalities (e.g. social media, weather, traffic patterns, local events) in the Demand Planning?
- Are all demands, including service parts, interplant, subsidiaries, new products, etc., included in total demand?
- Would the company be able to manage range forecasts instead of punctual ones?
- Does your business balance the forecast with the Supply and Operations plan?
- Are variations in actual demand/Supply from plan measured and root causes of variations determined and discussed?
- Does your business prepare several alternative scenarios in S&OP so that you can actively anticipate opportunities or threats?

- Are manufacturing product or process families defined by taking into consideration critical capacity and/or material resources?
- Is an Agile Methodology used?
- Is there early detection and fixing in each sprint and not at the end of the project?
- Is customer feedback given at the end of every sprint and not at the end of the project?
- Are there Executive Demand Planning meetings in place?
- Is the Executive Demand Planning meeting a decision taking meeting?
- Do CEO and CFO regard Demand Planning as a crucial instrument in achieving the company goals?
- Does your organization's Senior Leader chair and provide direction to the Demand Planning meeting?

For "Technology" perspective, the questions are:

- Is internal data easily available and accessible?
- Is data quality periodically checked and improvement plans developed?
- Is the company willing to store data on the cloud (matter of security)?
- Is data quality not creating issues in your Demand Planning process?
- Do you have a master data management team?
- Do you regularly have data synchronization meetings with key trading partners?
- Is the company not using spreadsheet-based tools for Demand Planning?

- Is the company using Demand Planning software solutions?
- Is the company willing to invest in new technologies to elaborate mass amount of data?
- Are there standard reports that show info and results of the process in a consistent way to users?
- Does your business use KPIs to monitor and evaluate Demand Planning process performance/forecast accuracy (e.g. Bias, Forecast Error, MAPE)?
- Are there standard KPIs in place calculated the same way in different countries and regions?
- Are there formal KPIs sets where the results are monitored, reported and used as drivers for performance improvements?
- Does your company analyze trends and gaps while reviewing KPIs within Demand Planning?
- Does your business have KPIs that effectively reflect the strategic direction, giving weight to standard KPIs according to their importance?
- Is your company using predictive analytics?
- Is predictive analytics used to support a segmented approach to supply chain management (so not just statistical forecasting)?
- Does your business forecasting solution automatically suggest the right level to forecast, recommend the correct algorithm for that segment and auto-tune the algorithm's parameters?

- Is the company taking actions to move towards prescriptive analytics?

For the "Change" perspective, the questions are:

- Does your business measure how well employees understand the Demand Planning process?
- Is change management considered a critical success factor within the company?
- Does your organization ask for your point of view on Demand Planning on a regular basis (trend monitoring)?
- Do you think people and organization are ready to undertake this change?
- Is top management involved in the change management process?
- Is there a plan to address resistance?
- Is there a formal communication plan to inform people on what is happening in Demand Planning?
- Does the communication happen on a regular basis?
- Does your business communicate what is happening with Demand Planning to employees using multiple communication channels?
- Does your business educate employees on solutions and processes (training)?
- Does your business use different teaching techniques at different levels to build sustainable knowledge of the Demand Planning process?

- Does your business segment the provision of Demand Planning education based on shareholders importance in the process (tailored education)?
- Does your business use 1:1 coaching for Demand Planning improvement?
- Is the company oriented towards a continuous improvement?
- Does your business measure the quality of each Demand Planning meeting with checklists?
- Is the company making use of demand Maturity Model/Assessment to understand possible improvements?

5.4.4 Scoring Method

The worksheet is divided into four sections corresponding to the different perspectives: People, Process, Technology and Change. Each section is filled with the respective questions and for each of them there are different columns: factor, weight, readiness gap and max score.

Each question has 3 responses, signifying 3 different levels of assessment. Choosing a response that signifies readiness/low-risk (Yes) gives a factor equal to zero. The high-risk response (Not at all) gives the maximum score possible (10) to the factor, while the medium risk response (To some extent) gives half the maximum risk score (5). The overall risk score, called “Readiness Gap” is calculated by multiplying the factor with the weight given to the question. The maximum possible risk score, called “Max Score”, is 10 times the weight.

At the end of each section the Readiness Gap Score (the sum of the Readiness Gap for all questions), the Maximum Gap Score (the sum of the Max Score for all questions) and the Scored Gap Percentage (obtained dividing the Readiness Gap Score by the Maximum Gap Score) are computed.

Attachment 3, at the end of this chapter, shows the "Change" section and its score.

5.4.5 Results Analysis

This Cognitive Demand Readiness Assessment Worksheet should be filled in by the Strategic Services Consultant after a meeting with the client. The results obtained are showed in this way:

		Scored Gap score	Maximum Gap score	Readiness Gap %
1	**People**	710	980	**72%**
2	**Process**	130	1110	**12%**
3	**Technology**	255	860	**30%**
4	**Change**	280	660	**42%**
	TOTAL	**1375**	**3610**	**38.09%**

Figure 5-27 Cognitive Demand Readiness Assessment results

People Gap Values			
0%	to	20%	limited risk
21%	to	60%	moderate risk
61%	to	100%	significant risk

Process Gap Values			
0%	to	20%	limited risk
21%	to	60%	moderate risk
61%	to	100%	significant risk

Technology Gap Values			
0%	to	20%	limited risk
21%	to	40%	moderate risk
41%	to	100%	significant risk

Change Gap Values			
0%	to	20%	limited risk
21%	to	60%	moderate risk
61%	to	100%	significant risk

Total Gap Values			
0%	to	25%	limited risk
26%	to	50%	moderate risk
51%	to	100%	significant risk

Figure 5-28 Cognitive Demand Readiness Assessment ranges

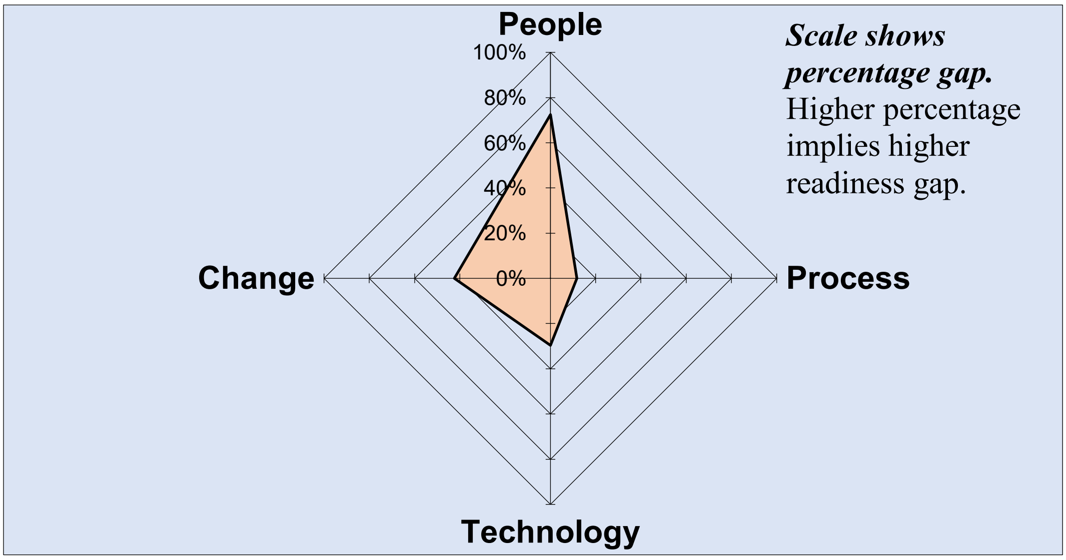


Figure 5-29 Cognitive Demand Readiness Assessment spider diagram

As we can see form Fig. 5-27, for each perspective the Readiness Gap % is shown, then the Total Readiness Gap % is calculated. The cells automatically become red/yellow/green based on defined ranges that can be tailored according to the type of client (see Fig. 5-28). The red color indicates that the company is not ready at all to implement the Cognitive Demand solution and this is linked to a level 1 of maturity (Firefighting). Yellow means that the company is positioned better in the maturity model, being at level 2 (Co-ordinating), but it probably needs to focus and improve in some radials to be successful with the implementation. Green symbolizes that the company is ready to take the next step towards Cognitive Demand, being at either level 3 or level 4 of the maturity model (Integrating/Synchronizing).

The result is also represented graphically thanks to a spider diagram in which a higher percentage corresponds to a higher readiness gap (see Fig. 5-29). This means that the client should focus first on the perspectives showing a higher percentage in order to improve its Demand Planning process.

After a discussion with the project team, the Consultant, based on the answers received and on the results of the assessment, should propose a mitigation plan to guide and allow the company in achieving the next maturity level.

5.4.6 Attachments

Attachment 1 – Demand Planning Maturity Model – People and Process Perspectives

		Demand Planning Maturity Stage			
Perspective	**Radial**	**Firefighting**	**Co-ordinating**	**Integrating**	**Synchronising**
People	**Sponsorship**	Senior business leaders are not supporting the development of a consensus plan.	Initial executive-level support for demand planning from senior supply chain leadership.	Integration between functional leaders to support consensus demand planning.	The CEO or business unit equivalent personally champions the Demand Planning process and chairs the Executive Demand Planning meeting.
	Organisational Design	Decentralized. Multiple owners for demand plan. Demand-planning role is part-time and the career track in this area is not clearly defined.	The Supply Chain functional leader has appointed one of their people as demand planner (in addition to their day job). Ownership of the forecast is established.	Centralized planning group fills in gaps between both interdepartmental and external plan numbers. A clear career path is developed.	Planning group supports the identification of new demand streams and segments, collaborative relationships with external partners.
	Focus & Objective	Focus on the fulfilment of immediate demand. Historical sales drive the forecast which is made on a volume-base at the category or product/family level.	Consensus demand plan at a lower level of detail, SKU level. Statistical forecast based on historical sales and internal insights.	Demand plan that includes external partners inputs and an appropriate scenario planning and risk assessment. Segmentation frameworks are developed.	Focus on a demand plan based on the creation of new demand streams that consider social and environmental factors, and on the development of strategies for sustainable long-term business growth.
	Culture	Silo views, lack of a single version of truth. Strong functional sub-cultures. Inside-out view of demand. Demand planning not considered a strategic process.	Functional and personal interest drives decision making. Some resistance is still present across functions. Internal collaboration starts at this stage, usually through S&OP process. Companies start to recognize strategic importance of Demand Planning.	Cross-functional teamwork is the norm. Recruitment, organisational design, people development and reward policies are designed to promote cross-functional team working. Ouside-in view of demand emerges. Demand Planning integral part of corporate strategy.	The process is embedded in the culture to such an extent that it survives changes of leadership and strategic direction.
Process	**Planning Horizon**	Short-term firefighting (1-3 months).	Medium-term view (6-18 months).	Horizon extends to 18-24 months.	Planning horizon driven by the needs of the business and can be determined by S&OP requirements or market demand. Companies have long-term visibility into product and service needs.
	Process Documentation	There is little documentation describing the Demand Planning process.	Processes start to become standardized. A documented Demand Planning process exists but has not been updated, with no formal revision cadence to keep current.	Demand Planning policy is documented and shared in a central repository ensuring version control: participants, responsibilities, timing, inter-dependencies and objectives are clear for each step.	Shared centralised " playbook" that documents key decisions, lessons learned, and optimal ways-of-working across the people-process-technology-change perspectives.
	Product & Portfolio	Product and service introductions are not co-ordinated across the business.	The forecast includes new products and services but the forecasts are not updated during the development process. Product and service complexity is addressed via one off sku reduction exercises.	The forecast includes new products and services (based on similar launch profiles and judgement). The forecasts are updated during the development process. Product and service complexity is addressed via one off sku reduction exercises.	Forecasts for new products and services evolve during development stages and as each gate is passed. There is a mix of judgemental and deterministic forecasting approaches. There is a reliable phase-in and phase-out process. Continuous review of the product and service portfolio within the S&OP process enables complexity to be managed.
	Demand	Each function has its own forecast. Heavy influence of sales and financial targets.	A consensus forecast process has been introduced incorporating insights from statistics, sales, marketing and finance. Demand forecasts obtained are used by S&OP and S&OE to make trade-off decisions.	A segmented approach to forecasting has been adopted. Forecast Value Add thinking has been utilised to improve the quality of the consensus forecast and eliminate bias. The forecast is expressed in whatever units (volume or financial) is required by users.	The forecast is enriched using cognitive insights such as SNEW (social media, news, events, weather).
	Supply	The supply function focuses on short-term supply issues and equipment utilisation.	Capacity and resource issues are now identified in advance because there is a constrained supply plan for the tactical horizon.	Alternative supply scenarios can be modelled to show the financial effects of adding capacity, transferring loads between plants, building ahead, shorting demand etc.	Communication is further enhanced with a Keystone Communication Message for each month and the use of external Demand Planning coaching for stakeholders.
	Project Management	The Waterfall methodology is used. Detection and fixing during system and regression testing at the last phase of the project. Customer feedback at the end of the project. Analysis and design should be completed for all stories before programming. Product Owner (PO) decides project scope.	The Iterative methodology is used. Early detection and fixing in each iteration for new features. Followed by regression testing. Customer feedback at the end of every iteration. Analysis and design should be completed for a "set of stories" before programming. Project Manager (PM) decides scope for iteration in consultation with Product Owner.	The Agile methodology is used. Early detection and fixing in each sprint followed by stabilization. Customer feedback at the end of every sprint. Stories that are not subjected to change, that can be completed (analysis to demo) within the sprint will be considered for the sprint. Team decides the sprint scope.	Same as Integrating level.
	Executive Decision Making	The Executive team is not involved in Demand Planning.	The Executive team may be called upon to arbitrate between demand and supply functional views.	The Executive team has a monthly Demand Planning meeting, but the meeting focuses on reviewing KPIs and standard reports. Decisions are postponed to future meetings because further analysis of options and scenarios is required.	The Executive team can make agile decisions. When a decision is taken it is rapidly and effectively communicated to the business so that the next Demand Planning cyle starts with a set of shared assumptions.

Attachment 2 – Demand Planning Maturity Model – Technology and Change Perspectives

		Demand Planning Maturity Stage			
Perspective	**Radial**	**Firefighting**	**Co-ordinating**	**Integrating**	**Synchronising**
Technology	**Data**	Data quality is poor.	Transactional data quality is good, but master data remains of variable quality. Presence of a System of Record (SOR), usually it is the ERP.	There are regular data quality improvement projects. Presence of a Planning System of Record (PSOR).	There is a centralised master data management system run by a Centre of Excellence team. Data is syncronised/exchanged with strategic trading partners.
	Solutions	Spreadsheet based tools.	Companies start investing in Demand Planning software solutions.	Technology used to enable both internal and external collaboration. Separation of long term and near term forecast.	Use of Machine Learning algorithms and sophisticated attribute-based modeling techniques that allow to process mass amount of external data, both structured and unstructured.
	Reports	Everyone has their own set of Excel reports.	A data warehouse is used to provide a single source of the truth for reports.	Standard reports are available allowing users to view information for their part of the business in a similar way to their colleagues.	In addition to standard reports, Demand Planning participants have access to user based dashboards showing action items, exceptions, scorecards and favourite reports and graphs.
	KPIs	Processes are informally monitored and corrective actions are based on severity of issues encountered. Little use of supply chain metrics. Forecast accuracy measured at product category/family level doesn't allow to take significant actions.	Standard KPIs are in place for much of the business. Forecast error and bias are tracked, but results are period specific and performance trends are not always formally monitored.	Formal KPIs set. Results are monitored, reported and used as drivers for performance improvements. Value-add of activities and data is tracked.	Business dashboards are in place that reflect the strategic direction of the business giving more or less weight to standard KPIs according to their strategic importance. Standard definitions for calculating KPI results are adhered to across the business. Metrics are co-owned with network partners.
	Analytics	Descriptive Analytics are standard across the business. Mass reporting and adhoc analysis is conducted across the business.	Predictive Analytics are limited to statistical forecasting.	Predictive Analytics is widely used in the organization to support a segmented approach to supply chain management.	Prescriptive Analytics is used to suggest potential resolution solutions to issues identified via Predictive Analytics. These guided resolution levers have been analysed by the system to ensure that their application will resolve the issue without causing a knock-on issue.
	Cognitive Insights	Historic and forecast data is the basis for all decisions.	Personal knowledge and insights from experts of different functions is used to manually improve forecast quality.	Use of externalites such as "influencer of demand" and use of a probalistic range for decision factors including risk management. Externalities can include social channels, weather forecasts, traffic data, video feeds, and IoT to manipulate and cleanse supporting data/information.	Automation of demand- supply-risk decisions with demonstrated and verified accuracy using the applications of Cognitive Demand, Machine Learning and Artificial Intelligence to move from Prescriptive Analytics into the Autonomous Supply Chain.
Change	**Change Effectiveness**	No measurement is in place to gauge the effectiveness of the Demand Planning change programme.	Measurement of Demand Planning change effectiveness is limited to completion of process checklists at meetings.	Metrics such as "I understand enough about the Demand Planning process to contribute effectively" have been developed, to try and understand stakeholder attitudes to and understanding of Demand Planning, but an adhoc survey doesn't allow trends to be monitored.	Regular Heartbeat surveys including questions on Demand Planning process understanding and support for the Demand Planning process are conducted amongst all stakeholders and the results are fed back to contributors. A core set of the same questions are used every survey to allow trend monitoring.
	Communications	No formal communications plan for Demand Planning.	A formal communications plan has been developed to help people understand what is happening in Demand Planning.	Use of multiple communications channels and mediums with continuous repetition in order to achieve cut-through for Demand Planning.	Communication is further enhanced with a Keystone Communication Message for each month and the use of external Demand Planning coaching for stakeholders.
	Scaffold learning	No Demand Planning education provided.	A one-time classroom education session has been run for project team members. User education is provided during User Acceptance Testing for the Demand Planning solution.	A scaffold approach has been taken to education with multiple different education vehicles being used to build upon each other in order to build deep sustainable knowledge about Demand Planning.	The scaffold approach has been further improved with segmentation allowing different user groups to have tailored education interventions. 1:1 coaching is provided for key stakeholders across the process.
	Continuous Improvement	No continuous improvement effort.	Process checklists are used at each meeting to ensure process compliance, and a regular cycle improvement meeting has been instigated.	The Demand Planning Maturity and Assesssment guide has been used to understand where improvement in Demand Planning is required.	The Demand Planning Maturity and Assessment guide is used on a regular basis supported by external coaching to ensure continuous improvement.

Attachment 3 – Scoring Method for Change Perspective

		0/1	factor	**Weight**	**Readiness Gap**	**Max Score**
4.00	**Change**					
4.01	**Does your business measure how well employees understand the Demand Planning process?**			4	20	40
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.02	**Is change management considered a critical success factor within the company?**			5	25	50
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.03	**Does your organisation ask for your views on Demand Planning on a regular basis (trend monitoring)?**			3	0	30
	◉ Yes	1	0			
	○ To some extent	0	5			
	○ Not at all	0	10			
4.04	**Is top management involved in the change management process?**			5	25	50
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.05	**Is there a plan to address resistance?**			5	0	50
	◉ Yes	1	0			
	○ To some extent	0	5			
	○ Not at all	0	10			
4.06	**Is there a formal communication plan to inform people on what is happening in Demand Planning?**			4	20	40
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.07	**Does planned communication happen on a regular basis?**			4	0	40
	◉ Yes	1	0			
	○ To some extent	0	5			
	○ Not at all	0	10			
4.08	**Does your business communicate what's happening with Demand Planning to employees using multiple communications channels?**			3	15	30
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.09	**Does your business educate emplyoees on solutions and processes (training)?**			4	20	40
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.10	**Does your business use different teaching techniques at different levels to build sustainable knowledge of the Demand Planning process?**			3	15	30
	○ Yes	0	0			
	◉ To some extent	1	5			
	○ Not at all	0	10			
4.11	**Does your business segment the provision of Demand Planning education based on stakeholders importance in the process (tailored education)?**			3	0	30
	◉ Yes	1	0			
	○ To some extent	0	5			
	○ Not at all	0	10			
4.12	**Does your business use 1:1 coaching for Demand Planning improvement?**			4	0	40
	◉ Yes	1	0			
	○ To some extent	0	5			
	○ Not at all	0	10			
4.13	**Is the company oriented towards a continuous improvement?**			5	0	50
	◉ Yes	1	0			
	○ To some extent	0	5			
	○ Not at all	0	10			
4.14	**Does your business measure the quality of each Demand Planning meeting with checklists?**			4	40	40
	○ Yes	0	0			
	○ To some extent	0	5			
	◉ Not at all	1	10			
4.15	**Is the company making use of Demand Maturity Models/Assessment to understand possible improvements?**			5	50	50
	○ Yes	0	0			
	○ To some extent	0	5			
	◉ Not at all	1	10			
4.16	**Do you think people and organization are ready to undertake this change?**			5	50	50
	○ Yes	0	0			
	○ To some extent	0	5			
	◉ Not at all	1	10			

Change:	**Readiness Gap Score**	**280**
	Maximum Gap Score	**660**
	Scored Gap percentage	**42%**

6 Conclusions

This thesis dealt with the development of a questionnaire to test the readiness of a company in implementing Cognitive Demand solution for Demand Planning.

After a short introduction, in chapter 2 and 3, trends in the supply chain industry are analyzed. Starting from the shape of the supply chain that is no more linear, but it is a grid with different inputs, outputs and links. The point of view, in an Omnichannel world, is customer-centric and a digital supply chain allows to achieve superior performances and higher customer satisfaction. New technologies, such as Machine Learning, are impacting and influencing supply chain processes.

In chapter 4 the implications of this new environment are highlighted: the need for Change Management, a transition cannot be successful if the focus is not on employees and their expectations are not managed. Then the impact on Demand Forecasting, which is the interest of this thesis, is analyzed. The uncertainty in predicting customer demand has grown and new technologies, such as Machine Learning applied to demand forecasting, can help to increase forecast accuracy.

Another important aspect is to consider the social impact of new technologies, a company should always ask itself “How can this technology improve the work of my employees?”. It must be seen as something supporting and not replacing them.

Chapter 5 is the heart of this thesis. The company where these months of internship were spent, JDA Software, is presented and the Porter’s 5 forces analysis of the industry in which it operates is conducted. The meaning of Cognitive Demand is explained, so the use of ML in demand forecasting that allows to leverage on Big Data and include in the forecast a large number of linked factors (e.g. Social Media, News, Events, Weather). A S.W.O.T. analysis of this solution is performed, the architecture of data partners is shown and the results from the Proof of Concept are analyzed. The acquisition of BlueYonder company, highly specialized in the use of ML to predict demand in retail industry, has changed some features of Cognitive Demand solution and these changes are reported.

After having defined what Cognitive Demand is and how it works, the focus shifts on the Readiness Assessment. The literature review, about different existing readiness assessment models, is followed by the definition of the framework used. The Demand Planning Maturity Levels are four: firefighting, co-ordinating, integrating and synchronizing. Within each perspective (People, Process, Technology and Change), the characteristics of each radial are described according to the maturity level. Then, the questionnaire is presented. It is made of 85 questions, grouped in the four perspectives. Through a scoring method, the readiness gap is computed for each perspective and, based on different ranges, the company will fall either in the green or yellow or red area. It is possible to identify which are the perspectives in which the company should put more effort in order to move to the green area and to be ready to implement the solution. The role of the consultant, who is conducting this assessment, is to guide the company in filling the gaps between their actual Demand Planning process and the desired one.

JDA is currently merging together its solution and the BlueYonder one and it is working to develop success stories not just in the retail industry.

BlueYonder expressed a strong interest in the Readiness Assessment and will soon test it with its clients. Changes to the Assessment will be made based on the results obtained.

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