Introduction to innovation analytics

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Chapter 1

Introduction

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Innovation analytics (IA) is an emerging paradigm that integrates advances in the data engineering field, innovation field, and artificial intelligence field to support and manage the entire life cycle of a product and processes. In this chapter, we have identified several possibilities where analytics can help in innovation. First, we aim to explain using a few cases how analytics can help in innovating new products to the market specifically through collaborative engagement of designers and data. Second, we will explain the use of artificial intelligence (AI) techniques in the manufacturing context, which progresses at different levels, i.e., from process, function to function interaction, and factory-level innovations.

1. Introduction

Data are a rich resource that helps decision-makers overcome various assumptions and intuitions from product development to customer engagement. With respect to product development, design and data specialists must work together to enable companies to develop new products and business processes. As we are all aware, companies are heavily investing in data and design capabilities; however, those firms that could effectively use design and data capabilities to understand the challenges will be able to innovate substantially.

Innovation is the driver of economic growth; several empirical pieces of evidences from different countries suggest that innovation supports companies to develop and maintain competitive advantage. Innovation can be classified either as incremental or radical. Incremental innovation refers to stepwise improvements within an existing technological approach, whereas radical innovation refers to entirely new concepts or new ways to think about a product or a process.

Advancement in analytics and development of artificial intelligence (AI) techniques helps companies achieve incremental and radical innovation. Companies at this digital age strive for success and it is essential to adapt to the advancements in the field of analytics and utilize it for their innovation journey.

Innovation analytics (IA) is an emerging paradigm that integrates advances in the data field, innovation field, and artificial intelligence field to support and manage the entire life cycle of a product and process. Innovation analytics will become an integral part of the entire innovation life cycle that helps in making smart, agile decisions and also accelerates the growth of the businesses. Different types of analytics have been reported in the literature. The main four types are descriptive, diagnostic, predictive, and prescriptive. With the emergent techniques, we have an impression that the future of innovation happening in product and process developed will be by utilizing predictive and prescriptive analytics. By utilizing the analytical environment, companies will be able to drive innovation in their operational process and this will help them to remain competitive and successful in their domain market. Using analytics, one will be able to identify the features that are most and least popular and this will help the companies to develop products that perform better, are cost effective, and improve their processes. This chapter aims to understand the several opportunities and challenges involved in relation to innovation analytics.

Analytics methods such as data mining, predictive models, and simulation will help the companies to identify patterns and help them to drive radical innovation. The data and insights available will help in revolutionizing product development processes and methodologies. Data and analytics not only help in the innovation but also help in developing new data-based business models that will have unique value propositions. Utilizing analytics for innovation, businesses and companies will be able to make smart decisions, and the current growth in the digital tools and technologies will support them to innovate and grow.

IA as shown in Figure 1 plays a critical role in helping businesses and industries in making smart decisions. Companies are required to innovate based on ever-changing customer requirements and several opportunities provided by technological developments. It can be summarized that analytics is essential for innovation and will need to be an important asset for the organizations to compete in the competitive market. Companies should give a prominent place for analytics in their innovation strategies. Predictive analytics and simulation can help drive valuable innovation and companies must use internal and external data to drive innovation and reap rewards by using the data effectively.

In this chapter, we will discuss several key aspects involved in Innovation and analytics with respect to product development and processes improvement. We will also cover the current literature reported in the field and discuss how innovation analytics makes an impact on the businesses.

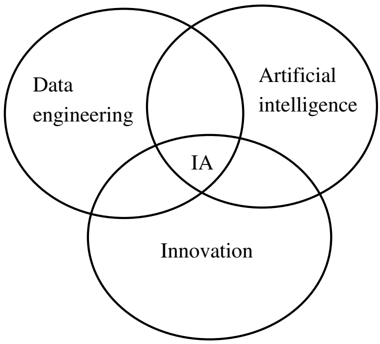

Figure 1. Innovation analytics.

2. Innovation Overview

Innovation is mainly a process by which businesses/organizations develop new ideas, products, and processes. It is an essential for any business to be innovative to thrive in a global market. Different types of innovation that any business can pursue are related to individual products, internal processes/workflow, and even business models. Companies can try achieving all these together in an ever-changing market. Companies like Apple are a great example for an organization that has been successful in embracing innovation in its lifetime.

As per the literature, innovation has several definitions. In this chapter, we use Thompson's (1965) perspective and define innovation as generation, acceptance, and implementation of new ideas, processes, products, or services. Innovation can be classified in several ways (incremental, disruptive, architectural, and radical). Two major categories commonly described in the literature are incremental or radical innovation. Incremental innovation deals with doing what the company does but doing it better. In case of radical innovation, it needs to be something completely new and different (Tidd & Bessant, 2020). Incremental innovation refers to stepwise improvements within an existing technological approach, whereas radical innovation refers to entirely new concepts or new ways to think about a product or a process. Radical innovation has a higher risk and may not be successful all the time.

It is crucial for businesses to be innovative; otherwise, they are faced with the consequences of being driven out of the market. In the last decade, digital and technological advancements have forced several businesses to be ready for change and expansion. Businesses must be willing to adapt and change. Innovation helps businesses to grow, makes them relevant in a constantly changing world, and differentiates them from other competitors. The main concept of innovation is doing something different from others by developing, updating products or by optimizing the processes involved to save time, money, and other critical resources to achieve a competitive advantage in the market. Businesses must think creatively and embrace innovation in their eco-system. It has been extensively reported in the literature that innovation models for businesses can be classified in different ways. Based on the size, age, and the sector, the reasons to innovate will vary. However, before embarking in an innovation cycle, the organization will need to understand the different innovation models that are reported in the literature. One such innovation model can be based on revenue. To achieve this, the products, services offered will need to be carefully analyzed by benchmarking with other companies' pricing strategies. It is also to be noted that innovation need not be only the radical change to the system. Another model of innovation will be based on identifying the processes, products, or services where businesses can improve the profitability by developing new partnerships, implementing new technologies, or even outsourcing specific tasks.

3. Analytics

Analytics was derived from the Greek word *analytika*, which translates to "science of analysis". With respect to business, it is the analysis of large sets of business data, through analytical techniques such as statistics, mathematics, and computer software and applications. Analytics helps in capturing the status and changing within and outside an organization. It helps in providing real-time and predictive insights. Analytics can help organizations to develop new products or improve the existing processes. Data and analytics help in understanding new trends, developing inventive approaches, and achieving innovation in product development and processes. These techniques help in identifying new opportunities for businesses. Data obtained from different sources in the business can help in innovating and improving the business performance. Using the data obtained, one could improve and simplify the decision-making and create an innovative impact on the business models. Different types of analytics have been reported in the literature. The main four types are descriptive, diagnostic, predictive, and prescriptive. Using descriptive analytics, one will be able to answer the following fundamental question: What happened? In such analysis, using the events that occurred in the past, one tries to identify specific patterns within the data. This analytic methodology forms the foundation of other analytic techniques. In the case of diagnostic analysis, the main question that one attempts to answer will be as follows: Why did it happen? In this analysis, the organization must understand what happened to identify why it happened. Therefore, once the organization gets a good understanding of the descriptive insights, they will be able to apply diagnostics to get a deeper understanding of the situation. Predictive analytics is a form of analytics used by companies to plan a future product path and it tries to answer the following question: What is likely to happen? In this type of analysis, one will be required to use algorithms, data mining, and data interpretation to understand the market and trends. In predictive analytics, a collection of Artificial Intelligence tools such as machine learning, pattern recognition, sentiment analysis, and emotion recognition will be useful for the process of prediction. The most advanced level of analytics is prescriptive, and in this level, the question that one aims to answer will be the following: What should be done? Tools and techniques such as graph analysis, simulation, heuristics, and machine learning can be used to analyze the data.

Businesses should understand how to bring innovative ideas to life. One way of achieving this is by developing skills that are necessary within the businesses and one such focus area is Innovation Analytics where one must understand the different types of analytics available and how they can help businesses in their innovation journey. Although there are several reported research studies discussing analytics, there is a lack of clarity on how analytics and innovation can be linked, and this book will aim to provide clear insights into this. The central theme of this book is how companies can gain enhanced insights from analytics in their innovation journey.

4. Review of Research Studies

Analytics plays an important role in the innovation process. The innovation process involves lot of research and data analysis. It is critical to use analytics to help and support the innovation process. Companies must use internal and external data to help in their innovation journey. Using internal data, companies can make incremental advancements, which is considered the most common way of incremental innovation. External data that are available will help in generating new perspectives about the market and the performance of the company.

Due to rapid changes in the market, radical innovations are coming into the mainstream. Analytics methods such as data mining, predictive models, and simulation will help the companies to identify patterns and these can help industries to drive radical innovation. Data and analytics not only help in the innovation but also help in developing new data-based business models that improve the value proposition.

In this section, we performed a quick review to present a few emerging use cases addressed by the researchers on application of analytic tools to enhance innovation process. In particular, we realize that people still explore the impact of analytics on innovation, such as handling big data, tensions between governance and innovation, green innovation, and competitive advantage to the firms.

To sustain open innovation challenges in small and medium enterprises (SMEs) and multinational enterprises (MNEs), Del Vecchio *et al.* (2018) analyzed the impact of big data and analytics and offered a list of trends, opportunities, and challenges. In continuation of the above, Božič & Dimovski (2019) examined the relationship between the use of analytics and innovation ambidexterity. They tested a model using data collected from medium- and large-sized firms in Slovenia, applying partial least squares modeling. The results showed that the use of analytics is positively associated with successful balancing between explorative and exploitative innovation activities, which in turn enhances the firms' performance. In the context of UK SMEs, Liu *et al.* (2020) identified the barriers of utilizing cloud-based analytics for customer-driven design innovation in their study.

From the governance and innovation point of view, Mikalef *et al.* (2020) discussed the role of information governance in data analytics for driving innovation. They tested their model by collecting data from 175 IT and business managers. The finding states that data analytics would have a significant impact on both incremental and radical innovation capabilities of the businesses.

Use of data analytics to achieve competitive advantage is well explored. On the other hand, Zameer *et al.* (2020) explored the impact of analytics on green innovation and green competitive advantage through empirical evidence. Similarly, Duan *et al.* (2020) applied absorptive capacity theory to understand how UK firms recognize the value of data and how data are used to achieve competitive advantage. Their findings confirmed that analytics plays a significant role in sustaining innovation and helps in developing new products with the inclusion of environmental impact as well.

5. Analytics and Innovation

Analytics will help in bringing all the departments of the organization from sales to R&D to jointly collaborate in the innovation process and decision-making. Analytics will help in validating the creative process and providing necessary insights to the product innovation as discussed in the following subsections.

5.1. *Product innovation*

Analytics is vital to product development mainly with focus on product improvement. Without using analytics, the product development team will not be clear on what needs to be achieved and will not be able to meet customer requirements. Different metrics and understandings provided by analytics will help the product innovation teams to make informed decisions and improve the product functionality.

By using analytics in product innovation, businesses will be able to test, learn, and remodify the product design and launch process. This helps the decision-making process to be objective, reliable, and faster. Analytics can provide the team with real-time product performance measurement and helps in creating an accurate roadmap of how the product performed and what factors are to be considered in the future. Such analytical tools can also help businesses to understand their competitive advantage and help in proving a holistic view to the product team. Analytics will be able to give the most complete picture possible and this can be used to build the best product possible for the future. Advances in data management, cloud computing, and Big Data business will be able to enter a new age of product analytics. The data and insights available will help in revolutionizing product development processes and methodologies.

Applying analytics is a collaborative process that involves all the stakeholders, and analytics is applicable through every stage of the product development life cycle. Analytics must be embedded into every phase of the product life cycle development to gather data and insights to drive innovation from various perspectives. In regard to product development, managers and product developers have several critical questions to answer such as identifying factors and attributes that determine the future innovation in the product development. They are expected to understand internal and external factors that are essential for the success of a product. Identification of factors that will help in optimizing the product innovation, keeping customer requirement in focus, is also necessary. Mostly, companies have a limited set of tools and techniques and they heavily rely on the trial-and-error approach. However, the advancement of analytics can help in improving the product development process. Traditional approaches such as CAD, DFMA, FMEA, and Value Stream mapping are essential tools extensively used by organizations to improve the efficiency, eliminate waste, and optimize the product development process. However, as products are becoming complex and there is an abundance of data generated, these traditional tools are not being enhanced by the big sets of data and advances in the AI field to drive innovation in their product development process. Using analytics, organizations can improve their R&D process and also develop and identify new products and market segments. By applying analytics, organizations will be able to obtain clear customer insights and help in targeting the right audience for their products. It also helps them to price their products competitively.

In relation to innovation in product creation, using analytics, one can improve the performance by classifying the key product and customer attributes. Using this, one can model the relationship between the commercial success and the attributes to develop new products. In product testing, analytics can be used to model the relationship between the key performance drivers of the past products and the commercial success expected. Organizations can use similar concepts when planning and executing product launches, where key attributes of past success will be able to provide clear insights into what has to be done to achieve success in the future. The key aspect concerning product development is to collect data of the key attributes and develop the relationship based on the measure of success expected. To achieve this, a consistent, disciplined approach is essential.

Predictive analytics has been in focus in the last few years. The concept of predictive analytics can better help to understand the market, demand factors, and customer requirements. The scope of predictive analytics is enormous and can help achieve innovation in product development. Predictive analytics has not been extensively used in the field of innovation primarily because it is time consuming to develop predictive analytical models. However, it is very evident that predictive analytics will be crucial to achieve innovation targets in every industry. In predictive analytics, historical data are used to model the key trends and patterns. Using this model with the current data, one could predict what would happen next.

Application of prescriptive analytics helps to advance the innovation process in product development to the next level. Based on the predictive analytics, data organizations get an idea of what will likely happen in the future, so in that scenario, the organization will be able to plan what should be done. Using prescriptive analytics, one can develop various courses of action and outline what the potential implications would be for each. Prescriptive analytics applies artificial intelligence and machine learning, which includes algorithms and models that will help computers make decisions based on statistical data relationships and patterns. However, prescriptive analytics systems are not flawless, and they need to be monitored very carefully. There are concerns regarding the quality of data available and this can lead to wrong predictions. In the near future, several departments in the organization can use prescriptive analytics to drive innovation in the product development process.

5.2. *Process innovation*

In today's fiercely competitive global economy, manufacturing companies need to take quick and innovative actions, for example, swiftly measuring shop floor performance, rapidly identifying and trying new ideas, and scaling at speed as they grow. These require vast troves of factory data and tools that can analyze the data and provide critical insights into how the shop floor needs to evolve. That is why manufacturing companies are moving toward artificial intelligence-based (AI-based) solutions as a catalyst for their shop floor digital transformation and the key to making the right decisions to grow their business (Arinez *et al*., 2020; Wang & Gao, 2020).

The manufacturing academic literature conceptualizes AI as a collection of tools that can extract insights from the manufacturing data and facilitate data-driven decision-making (Subramaniyan *et al*., 2021). AI revolution is transforming the traditional manufacturing practices leading to increased productivity (Lee *et al*., 2020). On the other hand, AI can help manufacturing companies innovate faster. For example, it can analyze interdependencies between humans, machines, robots, processes, and products more apparently by studying the data relationships. The new insights from these analyses can help shop floor engineers and managers to better understand the dynamics and make informed decisions.

Take the car manufacturing factory as an example. The factory will have several machines performing several operations (such as welding and painting) working together to manufacture a car. Consider this factory operation as a three-level hierarchical setup as described in Arinez *et al*. (2020). The bottom level, also called a process level, is where the tool interacts with the raw material to produce a car. At the middle is the machine level, where several components in a machine work together to execute a process. The top is the factory level, where several production resources, such as machines and robots, interact to establish a production flow.

At every level, engineers need to control numerous variables to produce a car. In addition, several variables at each level interact with one another, thereby increasing the complexity even more. Analyzing the variables and their interactions is necessary to identify the problems and design the solutions for productivity improvement. This is where AI can drive innovation. AI can explore all possible relations between the variables and hidden patterns that may not be readily observable by mining through the data. This leads to new insights and innovative solutions.

Let us look into how AI can drive innovation in eliminating throughput bottlenecks in a production system. Throughput bottlenecks are a high-frequency and high-impact factory-level shop floor problem (Subramaniyan *et al.*, 2016, 2021). Throughput bottlenecks are those machines or processes in the shop floor which constrain the shop floor throughput (Roser *et al.*, 2001). When engineers eliminate throughput bottlenecks, it is possible to get more throughput from the shop floor. In the real world, the engineers should identify the throughput bottlenecks almost daily and eliminate them to achieve the target throughput of the day. The traditional practice was to identify them through manual shop floor observations (Lee *et al.*, 2020; Subramaniyan *et al.*, 2021). This practice is time consuming and a manually intensive task. However, with the rise of digitalization and AI, identifying them has become an easy and less time-consuming task.

AI can create new knowledge about throughput bottlenecks on the shop floor and drive innovative elimination actions (Subramaniyan *et al.*, 2021). Consider a shop floor that has a serial production system of 10 machines. Every machine takes a set of states (e.g., producing, part-changing, blockage, and starvation) during the scheduled production time (Roser *et al.*, 2002). When engineers analyze these states and manipulate them (e.g., optimize the setup times), they can achieve higher throughput from the production system (Roser *et al.*, 2003). Consider that every machine assumed 10 distinct states during the production time. From a systems perspective, then there are 10^{10}, which is equivalent to 10 billion machine–state combinations. These massive combination sets are challenging to analyze manually. Usually, the shop floor engineers pick the throughput bottleneck machines in the production system based on their experience or simple static heuristics. This practice will not be effective because of the changing dynamics of the production system, for example, machines degrading with time and the introduction of new products and new machines changing the system dynamics. AI (e.g., deep neural networks) could help in these situations. AI can analyze every combination of the machine–state set, predict the combination that affects the system performance the most, and thereby identify the throughput bottlenecks. In this process, AI can reveal new information about the production system dynamics and throughput bottlenecks that is hard to capture by manual analysis. Engineers can use this information to design innovative solutions for eliminating bottlenecks and achieve the target throughput.

Analytics can play a key role in improving the project management process and can help in managing critical projects. Management of critical projects mainly deals with taking critical decisions and this can be supported by using analytics-based methods such as data mining and machine learning techniques. By analyzing the project data, one can make better decisions and also solve typical project-related problems. Using analytics, managers can predict early signs of deviations with respect to budget, cost, and time and take necessary corrective actions. Using analytics, one could estimate the progress of the work and also predict the possible completion time of the project.

Deeper and insightful analytics can improve the resource utilization and forecasting of cost and revenue. It is predicted that in the next decade, manual-based project management-related tasks will be taken over by analytics-based techniques. This does not mean that it will replace anyone's job; however, these techniques will help in making very informed decisions to improve the quality of the project execution with regard to time and cost.

Analytics will help in systematic quantitative analysis of data, and project managers will have the ability to optimize resource scheduling and allocation on projects. This will help them to propose the best possible schedule of resources with the available team. Using analytics, one could review the work and time-off schedules of all the people available at work and help in preparing weekly productivity reports. In short, analytics provides plenty of opportunities to optimize the project management implement process.

6. Summary of Chapters

We classify the 11 accepted chapters in this book as per the themes, namely, product and process innovation, artificial intelligence, and data engineering. This section offers a brief summary of chapters within each theme.

6.1. *Product and process innovation*

The first 4 chapters out of the 11 accepted discuss the application of emerging analytics for product and process innovation. The authors in *Chapter 2* have explored consumer product innovation and opportunities for data analytics. The focus of this chapter is to explain the possibilities for the use of AI-enabled tools and processes that can synthesize and mine social media data for innovation. In addition to the above, the study identifies practical barriers to using big data for innovation including in-house data analysts, siloed data sources, mismatch between product development and rapid change of consumer trends, and lack of integrated data mining capabilities.

The use of a system architecture computational tool to gather design data for developing an interdisciplinary product is explained in the *Chapter 3*. In particular, the chapter proposes a methodology based on function–behavior–state modeling and a computer-aided design system to customize the product at an early design stage.

Chapter 4 discusses business model innovation and potential application of innovation analytics. Use of social media data and the application of the same for a new business model targeting SMEs are explained in this chapter through an innovation process framework that emphasizes the need for capability development and multidisciplinary teams.

Smart manufacturing implementation and the role of product and process innovations are explored in *Chapter 5*. The chapter identifies 18 factors related to smart manufacturing implementation in the automotive sector that have a major influence on product and process innovations. The authors engage a VIKOR-based multi-criteria decision-making methodology to prioritize the factors.

6.2. *Artificial intelligence*

In terms of artificial intelligence, *Chapter 6* discusses the linkage between technological advancements and ubiquity. In particular, it seeks the potential application of artificial intelligence, non-routing algorithms, and visualization for innovation process. The chapter picks a hypothetical example of a start-up company that specializes in integrated circuit manufacturing to explain the innovative personalization process through customer data collection and analysis.

Chapter 7 narrates the analogy of human sensory organs with the industry Internet of Things and lists various enablers with respect to vision, sound, touch, smell, and taste/quality. In addition, the chapter reviews the popular machine learning algorithms such as unsupervised learning, supervised learning, deep learning, and reinforcement learning and their applications in product design, warehousing, and logistics and core manufacturing. The authors also suggest a few futuristic applications such as digital twins, edge computing, and technological aspects.

Chapter 8 reviews the potential application of artificial intelligence to analyze the food characteristics data generated through Internet of Things interconnected sensors to reduce food waste. The chapter also suggests various criteria to select the right AI tool for IoT implementation and its scalability to other sectors.

The role of machine learning and machine reasoning for intelligent transport systems is discussed in *Chapter 9*. Using case studies and surveys, the authors demonstrate the use of data generated through latest technologies such as video imaging and thermal imaging for better traffic management. The authors select Portland as a reference and explore the use of data analytics to manage traffic without any hassles.

6.3. *Data engineering*

Chapters 10–12 discuss the developments in data and they include the role of big data, evolution of time series data, fuzzy data, and textual data. A brief summary of each study is given as follows.

Chapter 10 explores the innovative solutions to reduce multiple corrections in the forecasting support systems. Specifically, the study discusses the process innovation in forecasting and inventory management. Through a survey, the study identifies the 11 most common drivers that necessitate the frequent adjustments made in the forecasting time series data and the use of exponential smoothing methods used in multiple industries.

Chapter 11 proposes a newer method to deal with fuzzy data in the selection of alternate designs in an open innovation process. The chapter reviews the use of multi-criteria decision-making for evaluating the appropriate design for mobile robot chassis, considering criteria such as novelty, manufacturing cost, assembly time, design complexity, and manufacturing feasibility.

Chapter 12 analyzes the forecasting method for innovative products. The authors identify the impact of electronic word-of-mouth criteria to predict the most preferred products by the customers. The authors explain Facebook's prophet forecasting model to identify the nonlinear trends on daily basis.

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