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The Future of Digital Business Innovation

Trends and Practices

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Foreword

The Digital Revolution is one of the *buzzwords* in 2015 among both academics and practitioners. Coping with the Digital Revolution requires members of an organization to adapt to new measures, something individuals do not always find easy. The challenges of innovation in increasingly digitized businesses require a clear understanding about the role of IT in the definition of business models—what are the (possibly new) targets, which resources should be involved, and where should investment be centralized?

A strong understanding of *what's out there* and an intelligent use of appropriate business models are necessary to enable the alignment and convergence among vision, strategy, and resources of any company to then clarify and simplify governance choices, to weigh up the value of resources, and to define the correct policies that complement the organization's operations.

This book identifies the challenges, ideas, and trends to provide a "management toolkit for survival" in the Digital Revolution. The first part deals mostly with the technological trends emerging from the increased use of intelligent computers and advanced IT platforms and discusses topics like wearables, machine-to-machine communication, the emergence of digital currency, and data visualization and security.

The Internet of Things or *smart objects linked to the Internet* and in particular the proliferation of wearables are extremely interesting and insightful to understand seemingly irrational consumer behavior. Machine-to-machine communication complements and, in part, substitutes the human factor in manufacturing and is likely to represent a USD200 billion industry by 2020.[1] The opportunities of this phenomenon seem limitless.

Digital currency destabilizes the concept of money dating back to the beginning of civilization. Virtual currency was defined only 3 years ago—in 2012—by the European Central Bank as "a type of unregulated, digital money, which is issued and usually controlled by its developers, and used and accepted among the members of a specific virtual community" and may soon replace traditional

[1] Source: http://www.statista.com/statistics/295685/m2m-total-industry-size-worldwide/

currencies even without a legal tender. Finally, digital transformation also requires dealing with much more data than ever before but not with more value de facto.

Everybody talks about volume, velocity, variety, and veracity, but few deal with the business relevance of data visualization, which is also discussed in the first part. Finally, Part I closes with the discussion of one of the most challenging and social aspect of digital business: the protection of organizations by malevolent attacks through an improved attention to digital security.

The second part highlights the main managerial trends that effectively address the trends identified previously. It takes the reader on a journey through neuro-information systems, IT ambidexterity, and IT-Business alignment evolution. Recent progresses in cognitive neuroscience are exposing the neural bases of cognitive, emotional, and social processes and give new insights into the complex interplay between IT and information processing and decision making in business-related situations. The importance of ambidexterity and the use of market information to obtain competitive advantage also represent an important tool of successfully dealing with Digital Transformation and can eventually form a new basis for a better development of the IT role in the company.

Finally, the third part of the book discusses, through structured case studies and business evidence, global innovation initiatives in 2015. This last chapter provide a guideline for different possibilities of innovation practices in the digital context.

This book provides a uniform understanding of the challenges and opportunities of trends and practices in digital business innovation, and most importantly, it provides readers with the right stimuli to take a first step towards change.

Ludwig-Maximilians-Universität München Tobias Kretschmer

Preface

In this book, we aim to discuss and present the main challenges and trends for the future of Digital Business Innovation to a composite audience of practitioners and scholars. This volume follows the one published in 2014 for Springer, aiming to fill a similar gap [1]. Indeed, looking at the state of the art, we believe that it is still yet difficult, as actually it was two years ago, to find a unified survey of current scientific and managerial work having an impact on future business, which also considers the diverse perspectives characterizing the Information Systems research (from management to computer science and engineering, among others). Such a summary should be suitable to be used by practitioners in their day-to-day activities or simply as an update on what the state of the art in academia and managerial contributions may offer with regard to future IT strategy as well as business value propositions in different industries. Indeed, it is worth noting that today as in 2014, notwithstanding journals such as MIT Sloan Management Review, IEEE Spectrum, or the Communications of the ACM (CACM) have such a mission of connecting research and industry practices, to the best of the author's knowledge they do not provide a yearly integrated review, encompassing all their respective areas (management, engineering, and computer science).

However, these publications are going to be part of the usual large body of knowledge together with journals, such as Management of Information Systems Quarterly (MISQ), Journal of Association of Information Systems-JAIS, Management of Information Systems Quarterly Executive (MISQE), Information Systems Research, European Journal of Information Systems, Journal of Information Technology, and the Journal of Strategic Information Systems, and conferences, such as International Conferences of Information Systems (ICIS), European Conferences of Information Systems-(ECIS), Americas Conferences of Information Systems (AMCIS), among others (just to mention the Management of Information Systems research sources), which this book aims to consider for identifying the challenges, ideas, and trends, that may represent "food for thought" to practitioners. Accordingly, each topic considered is analyzed in its technical and managerial characteristics, also through the use of case studies and examples.

Outline of the Book

The book's argument is developed along three main axes, following the same macro structure adopted in [1, 2]. In particular, we consider first (Part I) Digital Systems Trends issues related to the growing relevance, on the one hand, of machine intelligence (Chap. 1), wearable technologies (Chap. 2), digital currencies, and distributed ledgers for business (Chap. 3); on the other hand, a specific attention is devoted to data visualization (Chap. 4) and digital security (Chap. 5) trends and challenges for understanding organizations and user behavior, needs, and digital services/products requirements.

Subsequently, Part II considers Digital Management Trends, focusing on the impact of neuroscience for management of information systems, with a focus on the area of Neuro-Information Systems (Chap. 6), the role of IT ambidexterity in managing digital transformation (Chap. 7), and how IT strategy and alignment are reconfigured by digital business (Chap. 8). Finally, Part III of the book presents and reviews cases of Digital Innovation at a global level in a section called Innovation practices. Thus, the book adopts a scientific approach as for methodological rigor; however, it is also concrete and describes problems from the viewpoints of managers, adopting a clear and easy-to-understand style for the flow of the discussion as well as the arguments treated, in order to capture the interests of managers.

In summary, this book and the other former volumes on digital trends and Big Data and analytics [1, 2] are ideally connected as subsequent stages of a journey across digital business innovation; consequently, in line with the former stages' value propositions for the reader, this book also aims to be unique for its intention to synthesize, being a simple yet ready to consult scientific toolbox for both managers and scholars.

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2. Morabito V (2015) Big data and analytics. Springer, Heidelberg

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Contents

Acronyms

3D	Three-dimensional
AD	Advertising
AI	Artificial Intelligence
API	Application Programming Interface
ATM	Automated Teller Machine
BYOD	Bring Your Own Devices
CEO	Chief Executive Officer
CIO	Chief Information Officer
CMO	Chief Marketing Officer
CPU	Central Processing Unit
CTO	Chief technology officer
DNA	Deoxyribonucleic acid
DNS	Domain Name System
GPS	Global Positioning System
GPU	Graphics Processing Unit
ICTs	Information and Communication Technologies
IO	Input/Output device
IP	Internet Protocol address
IS	Information Systems
IT	Information technology
NATO	North Atlantic Treaty Organization
RFID	Radio-frequency identification
SaaS	Software as a Service
TV	Television
URL	Uniform Resource Locator
US	The United States
VR	Virtual reality

Part I

Digital Systems Trends

Machine Intelligence

1

Abstract

Machine intelligence and Artificial Intelligence (AI) are concerned with developing software as well as machines that have the capability to learn and to simulate humans' intelligence. Enterprises from wide range of industries employ AI technologies to get insights and discover patterns from large pools of data so they can provide better services to their customers. Similarly, factories utilize smart machines and robots to automate and optimize the manufacturing process, which yields better products for their consumers. Advancements in the intelligent computing capabilities have significant impact on how businesses can streamline their processes. The current state of machine intelligence as well as its applications in different types of industries will be discussed in this chapter.

1.1 Introduction

The increasing demands for improved services and better products as well as the continuously changing requirements from customers have added additional challenges on organizations to meet these expectations. This means that businesses need to have more flexibility to streamline their services, redesign their products and reconfigure their production lines in order to address rapidly changing market's demands [1]. Accordingly, the need for smarter machines and systems has emerged. Such situation has provoked professionals and researchers to employ the advancements in Artificial Intelligence (AI) as well as its techniques and applications in industry. By doing so, enterprises hope to gain the competitive edge that helps them to stay ahead in the market. The terms artificial intelligence and machine intelligence encompass several techniques such as *Knowledge based systems*, *Machine Learning*, *Deep Learning*, *Expert Systems*, *Data Mining*, *Genetic Algorithm*, *Neural Networks*, *Natural Language Processing* (*NLP*) and *Fuzzy Logic*. In other words, artificial intelligence can be seen as the enabler of the

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machine intelligence. Moreover, the research in AI area combines supplementary areas such as Computing, Math and Cognition among others [2].

- *Knowledge based systems*: They are the first step towards emulating human intelligence in a manufacturing context. They contain a reservoir of experts' knowledge about a specific domain, which can be consulted as needed [1].
- *Neural Networks*: The basic idea behind Neural Network is to emulate the way human brain works in using historical data to train the network in order to make decision in the future [3].
- *Fuzzy Logic*: It provides a way to represent or quantify degrees of truth while judging uncertain information such as texts, which cannot be evaluated with only true or false [1].
- *Genetic Algorithms*: They are the heuristic search algorithms that simulate the process of natural selection in humans' genetics in order to select the optimal options and eliminate the solutions with least possibility to succeed [1].
- *Natural Language Processing* (*NLP*): It is one of AI's branches that is concerned with studying how could machines and humans interact using the people's natural languages [4].

Utilizing machine intelligence in industry requires meeting the standards of the well-known *Turing test*, which was introduced by Alan Turing in 1950 and represents the machine's ability to simulate human's behavior in solving problems [5]. Other researchers [6] have envisioned that the intelligent machines in the future would go beyond the machine intelligence capability represented by *Turing test*. Hence, the intelligent system would not only be able to solve familiar problems, but also, will be able to predict and infer solutions in order to tackle new challenges [7].

The chapter is structured as follows: Sect. 1.2 discusses intelligent and expert systems. Section 1.3 will cover machine learning and deep learning and the difference among them. Section 1.4 presents data mining and pattern recognition including the methodologies that can be followed to gain the required business insights. Section 1.5 will provide examples of machine intelligent applications in healthcare and manufacturing. Section 1.6 highlights the importance of machine intelligence for "smart" industries. Section 1.7 clarifies some challenges that face the development and application of machine intelligence. Section 1.8 presents two case studies were the application of machine intelligence was successful and resulted with benefits for the businesses. Finally, Sect. 1.9 concludes this chapter.

1.2 Intelligent and Expert Systems

Intelligent and expert systems are important examples of decision making support software that represent AI application in industry. They help organizations in many ways such as improving decision quality and solving complex problems. Such systems use complex combinations of extracted knowledge and expertise that are

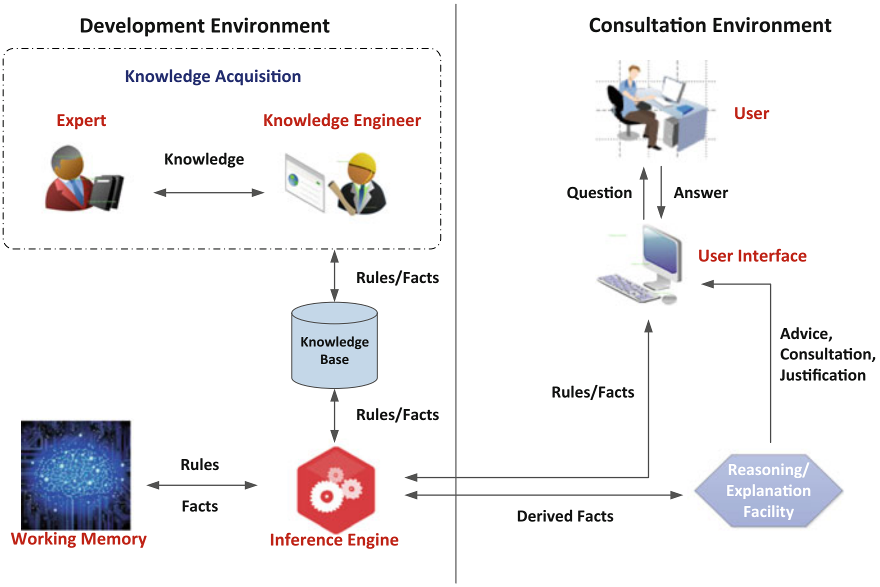

Fig. 1.1 Overview of the steps constituting the KDD process, adapted from [9]

generated from previous experiences in order to make inferences about the problem in hand and find best solution for it [8].

Expert systems powered with AI advancements in areas such as, e.g., Fuzzy Logic (FL) and Neural Networks (NN) among others, could bring the desired precision in market analysis and forecasting [9, 10]. Figure 1.1 illustrates the classic Expert System (ES) architecture, which is composed of two interrelated environments: the *development*, where the knowledge base is continuously updated by the knowledge engineer, as well as the *consultation*, where end users interact with friendly system's interface to acquire the best solution that is based on expert's knowledge of the problem in hand [9].

The way expert systems work places many challenges in constructing and developing the three main elements of an expert system: *knowledge base*, *inference engine* and the *user interface* [11, 12]. For example, developers have to find approaches to continuously maintain the expert system by communicating the new rules emerging form new experiences and projects to the knowledge base easily and as promptly as possible in order to ensure that the expert system is providing up to date advices [9].

1.3 Machine Learning and Deep Learning

Machine learning refers to the field of study that is concerned with utilizing the advancements in computing abilities, statistics and patterns detection in order to supervise computers and machines to learn from data and make feasible predictions about the future trends [13]. This is particularly helpful when the generated data are massive and they are beyond human's ability to process and understand [14]. Additionally, *interactive machine learning* brings more reliability to the prediction results. Actually, this is because the development and training of the machine learning systems occurs in this case within the same context they will be applied in [13], in contrast to the traditional methods of developing machine learning software in one context and using them in a different one.

However, despite the promising benefits that machine learning can bring, there are some challenges that need to be considered when applying machine learning techniques on large scale data [15]. One example of these issues is the speed and efficiency of the learning algorithms while extracting and accumulating knowledge as well as the ability of those algorithms to handle fast generated and streaming data. This issue is particularly important because of the limitations imposed by storage media [16], which make it essential to process the data as it is streaming and before they are summarized and saved. A good business example of such large and fast generated data is users' interactions with e-business websites such as Amazon in order to provide future recommendations on the products depending on the users' previous browsing history.

Deep learning on the other hand, is the branch of machine intelligence that focuses on utilizing neural networks to enhance image and speech recognition technologies by utilizing backpropagation algorithms to train multi-processing architectures for better pattern recognition. Deep learning differs from machine learning in that it is mainly unsupervised and that is why is considered the advanced level of machine intelligence [17]. Deep learning promises to have more applications in the future especially when it is combined with other technologies such as reinforcement learning and *Recurrent Neural Networks* (*RNNs*). The expectation from such combinations is (i) to perform better categorization related tasks that are based on machines' vision as well as (ii) to have improved natural language understanding which would enable the machine to understand spoken sentences and large sets of data [17]. Deep learning algorithms helps in extracting meaningful abstract representations from large amounts of unlabeled and unsupervised data making them attractive for extracting meaningful patterns from what are actually Big Data. Once these patterns are learnt from unsupervised data with Deep Learning, conventional discriminative models can be trained with supervised and labeled data entries, where the labeled data are obtained through human or expert knowledge. Deep learning algorithms are well suited to deal with Big Data issues especially large volumes with different structures [18].

1.4 Data Mining and Pattern Recognition

Data mining is the set of rules, processes and algorithms that are designed to find valuable "knowledge" in large data warehouses. It involves techniques for automated data processing and extraction that are supported by advancements in

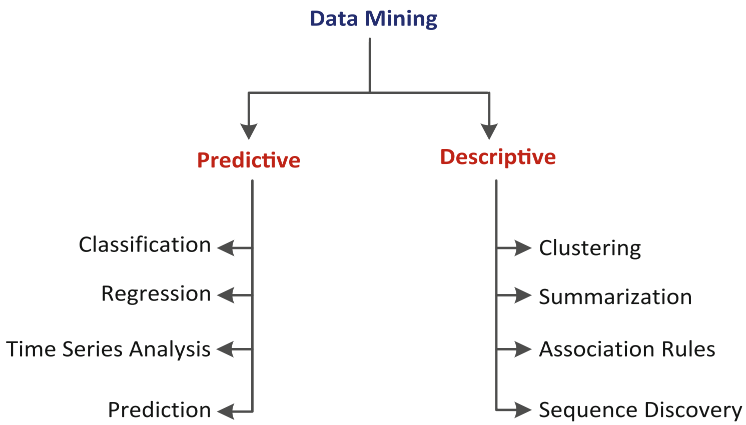

Fig. 1.2 Data mining models and tasks, adapted from [21]

artificial intelligence, statistics and machine learning to discover hidden relationships among variables within a database [19]. Data mining provides several opportunities for businesses to be competitive in the market by uncovering valuable insights from the data [20]. This is of particular importance when the required insights are needed from large datasets or Big Data. Figure 1.2 summarizes data mining tasks and techniques that fall under either predictive or descriptive models and that can be used to uncover information with potential value from millions of various medical records [21].

There are several methodologies or research approaches that can be employed to investigate (Big) Data from the above discussed mining perspectives, either in a scientific domain or in a business context. Among these few methodologies are worth mentioning the *Knowledge Discovery in Database* (*KDD*) [22], the *Sample, Explore, Modify, Model and Assess* (*SEMMA*)[23], and finally the *CRoss-Industry Standard Process for Data Mining* (*CRISP-DM*) [24]. The decision on which approach to use depends mainly on the industry and the type of the insight required from the Big Data [25, 26]. The following three subsections will explain these methodologies in details.

1.4.1 Knowledge Discovery in Database (KDD)

Knowledge Discovery in Database (KDD) can be described as the nontrivial extraction of hidden, novel, previously unidentified, and promising information from data [22]. The importance of KDD becomes more prominent when dealing with large data sets that exceed normal human capacity to analyze [22]. KDD encompasses a set of intelligent techniques such as discovery algorithms to uncover patterns and produce valuable information [27], thus employing different approaches that help in exploring the data. These include probabilistic, statistical,

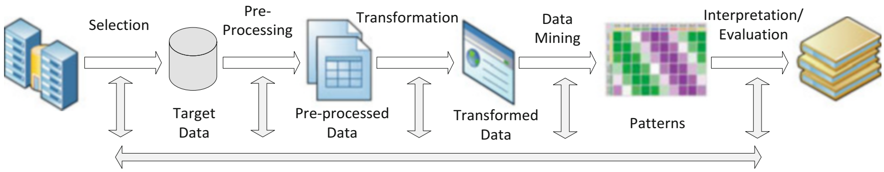

Fig. 1.3 Overview of the steps constituting the KDD process, adapted from [28]

classifications and decision tree approaches as well as neural networks and hybrid approaches that combine more than one method to get the insights [22].

As for these methods, it is worth mentioning that researchers in [28] have produced a process model for the KDD methodology as shown by Fig. 1.3, which illustrates the essential steps to discover the hidden knowledge. The basic steps in the figure are about (i) selecting the data that need to be examined, (ii) preparing and (iii) transforming the selected data to a proper form that can be mined using the chosen data mining model, and finally (iv) to interpret the discovered patterns in order to (v) extract valuable information.

According to Fayyad et. al. [28], the complete steps that represent this model are:

1. *Learning the application domain*: Realizing the prior knowledge and the aims of the process.
2. *Selecting the target dataset*: Choosing the subset to perform data discovery on.
3. *Data cleaning and pre-processing*: It includes removing noise, handling missing data and managing time sequence information as well as DBMS related issues.
4. *Data reduction and projection*: Deciding on the useful feature to project data as well as on the data reduction techniques.
5. *Choosing data mining method*: Which includes deciding the purpose of the data mining such as summarization, classification or clustering.
6. *Selecting data mining algorithm*: This includes selecting and matching data mining methods with the criteria of the KDD process.
7. *Data Mining*: Applying the selected data mining method to discover patterns.
8. *Interpretation*: Understanding the discovered patterns.
9. *Utilizing the generated knowledge*: This includes applying the knowledge in a system or process.

Moreover, other researchers [29] have proposed an extended version of the previous KDD model, which incorporates the data collection step as the initial step for the whole process and it involves collecting relevant data from multiple resources into one big data set and make it available to work on. Healthcare domain is one of the prominent examples of employing KDD methodology in a business context to transform healthcare related data into useful information [30]. Additionally, KDD proved to be of a great success in other industrial fields such as fraud detection, marketing and customer retention [30].

1.4.2 Sample, Explore, Modify, Model and Assess (SEMMA)

Sample, Explore, Modify, Model and Assess (SEMMA), illustrated in Fig. 1.4, is an industry generated sequential steps that guide the implementation of data mining techniques [23]. It is developed by SAS and is adopted by their main products for data mining, such as SAS Enterprise Miner.

The first step in this process is about extracting a sample data on which analysis is going to be applied. Once the sample is selected, the second phase is about exploring and searching the sampled data for strange trends and anomalies with the aim of simplifying the model. The third stage involves preparing the data for modeling by selecting, creating, and transforming the variables.

Them, the fourth step involves applying data mining techniques on the prepared variables. Finally, the last phase is about evaluating the generated results by analyzing the model by either contrasting with other statistical models or new sample in order to specify the model's reliability and usefulness [24]. SEMMA has been applied successfully in pharmacovigilance [31] and churn analysis in telecommunications industry [32, 33].

1.4.3 Cross-Industry Standard Process for Data Mining (CRISP-DM)

This methodology is also an industry generated guideline to perform data science research on large data sets and it is argued that it is the most used strategy for data mining project [25]. CRISP-DM, represented by the model in Fig. 1.5, is a comprehensive data mining approach and process model that provides researchers and practitioners with a full lifecycle plan for conducting a data mining project. As shown in Figs. 1.5 and 1.6, this methodology is broken down into six phases [24, 34], which are:

1. *Business Understanding*: This phase is about understanding project objectives and requirements, which would be converted to data mining problem definition and requirements.
2. *Data Understanding*: This phase is about initial data collection and familiarization. It helps to articulate data quality issues and to produce initial results.

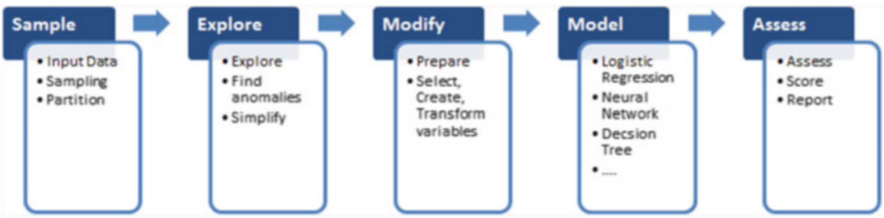

Fig. 1.4 SEMMA steps

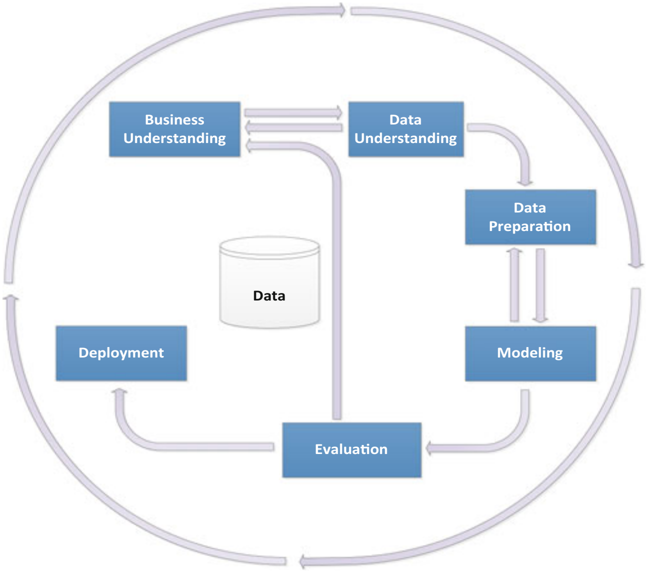

Fig. 1.5 CRISP-DM methodology, elaborated from [34]

Business Understanding	Data Understanding	Data Preparation	Modelling	Evaluation	Deployment
• Determine Business Objective	• Collect Initial Data	• Collect Data	• Select Modelling Technique	• Evaluate Results	• Plan
• Assess Situation	• Describe Data	• Clean Data	• Generate Test Design	• Review Process	• Monitoring & Maintenance
• Determine Data Mining Goals	• Explore Data	• Construct Data	• Build Model	• Determine Next Steps	• Produce Final Report
• Produce Project Plan	• Verify Data Quality	• Integrate Data	• Assess Model		• Review Project
		• Format Data			

Fig. 1.6 The phases and tasks in CRISP-DM methodology, elaborated from [34]

3. *Data Preparation*: During this phase, many data related tasks are to be performed. These include select, clean, construct, integrate, and format data. The aim here is to cleanse and prepare the data for modeling in the next step.
4. *Modeling*: In this phase, data mining tool will be used to apply the appropriate modeling techniques on the data generated before.
5. *Evaluation*: This phase aims to determine if results meet business objectives and to identify business issues that should have been addressed earlier.
6. *Deployment*: This phase is in charge to put the resulting models into practice as well as to set up for continuous mining of the data.

Also, the detailed tasks for each of the phases in Fig. 1.5 are represented diagrammatically in Fig. 1.6. Following these phases and tasks would ensure that data scientists could construct the proper data mining model and would acquire the desired results. CRISP-DM methodology application within the context of clinical research and especially the Neonatal Intensive Care Unit (NICU) can help clinicians to discover valuable information among the patients at the beginning of disease and other medical conditions [35]. This methodology can be used in various business domains when the goal is to discover interesting hidden patterns from huge amount of enterprise systems' data such as ERP systems [24, 36].

1.5 Applications of Machine Intelligence in Industry

Since the outset of the artificial intelligence, several industries and business sectors such as healthcare, education, bioinformatics as well as production planning and management have applied machine intelligence to automate many of their processes. Actually, it may enable potentially all kinds of businesses to accomplish jobs that were only possible to achieve by humans. Additionally, it provides means to perform tasks that require power that is beyond people's capacities, such as, e.g., processing and analyzing large sets of data [37].

Thus, businesses could make use of several advantages that AI can bring to them. Yet, they can depend on the machines that are enhanced with artificial intelligence without any necessary interruptions as in the case of humans. Additionally, smart technologies are emotionless, thus, they provide a rather unbiased support to decision makers. Finally, training one machine to do what another machine does is from a certain point of view much easier than training new people [38]. This section discusses the applications of machine intelligence in two important examples of business sectors.

1.5.1 Artificial Intelligence (AI) in Healthcare

Artificial intelligence has made impressive improvements in many healthcare related applications. The new developments and innovations, which are related to image processing and recognition, have enhanced and enabled a huge progress in the science of radiology [39]. Thus, doctors and technician within this specialty are capable to use smart Magnetic Resonance Imaging (MRI) equipment to diagnose diseases.

Moreover, the adoption of complex data analysis algorithms has provided several tools to investigate the medical records of millions of patients in order to identify trends related to diseases and symptoms and act as quickly as possible in the critical situations [40]. Additionally, the embedded intelligence within nowadays' smart wearables has allowed doctors to monitor the health conditions of their patients remotely [41].

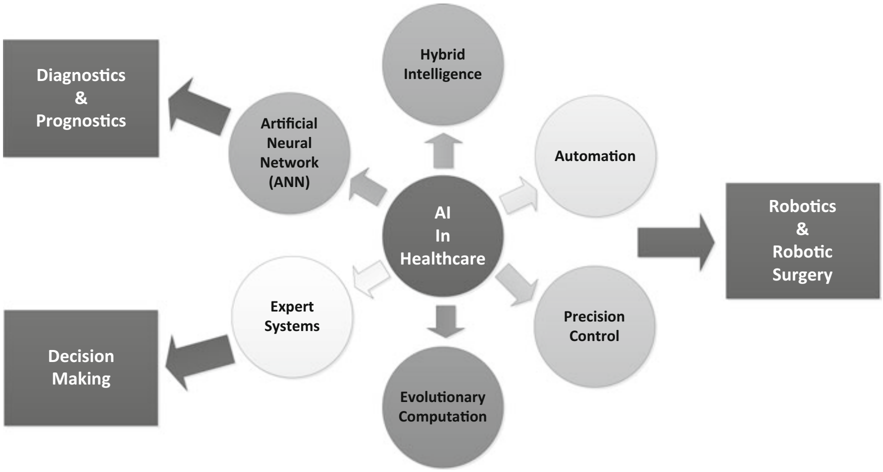

Fig. 1.7 Artificial Intelligence (AI) in Healthcare, adapted from [39]

Consequently, the vast amount of collected data such as health records, MRI images, genomic information, medical prescriptions and the live information from the wearables have enabled scientists to create health plans to deal with special kinds of diseases or people.

As for these issues, Fig. 1.7 illustrates an overview of AI technologies as well as their applications in the healthcare sector as proposed by [39].

1.5.1.1 Smart Wearables and Healthcare

The computing capabilities embedded in the smart wearables have offered several opportunities for those working in and benefitting from healthcare systems. One example of these advantages is the ability to record and monitor physiological information over long period of time as well as to accomplish this task in the original environment of the patient. Additionally, by monitoring the required medical information for a long time, the implanted intelligence system is capable to improve the judgement on the significance as well as the severity of the documented medical data [41].

Finally, the advanced wearable medical systems promise to provide feedback that is based on health condition and life style. Consequently, people would be able to change their daily habits to comply with their health situations [42].

1.5.1.2 Intelligent Robotics in Healthcare

The rapidly advancing and developing research in the field of AI has enabled new prospects and inventions that made it possible to utilize smart robots in the healthcare sector. These intelligent machines are now capable to accomplish many of what is used to be only achievable by humans.

For example, with the help of advanced robotics arms such as Davinci and CyberKnife, doctors are now able to perform invasive surgeries with higher levels of precision and accuracy [43]. Additionally, intelligent nursing assistants, such as RoNa, provide so much help to nursing staff with daily tasks, such as moving and lifting of patients [44]. Moreover, special robots can help with equipment and supplies transformation within hospitals and medical centers which would save man power required for these tasks [45].

1.5.1.3 Data Mining in Healthcare

Data mining techniques help with discovering hidden information with possible value in huge amount of data, which results in improved decision making process. It has several applications in the healthcare sector. For example, specialists can use data mining to compare data related to diseases and the symptoms as well as the medicines and treatments. Thus, they can evaluate the effectiveness of the treatments' strategies and to be able to plan for better services and health management especially in the cases of people with serious and chronic diseases [46]. One specific application of data mining in healthcare is using its techniques to discover patterns related to heart diseases in order to achieve higher accuracy and precision when predicting the possibilities of heart attacks [47]. This can be accomplished by mining patients' medical information such as age, gender and blood pressure [48]. Another example is mining lung cancer patients' data such as demographic information, ethnic backgrounds and medical history in order to have an improved decisions related to healthcare resources utilization [49].

In other words, data mining techniques and algorithms help to improve medical procedures, increase patients' satisfaction and decrease the number of unnecessary prescriptions and frauds [50].

1.5.2 Artificial Intelligence (AI) in Manufacturing

The different technologies of Artificial Intelligence (AI) have enabled a variety of applications in manufacturing related disciplines. Factories around the globe have employed AI for different kinds of manufacturing planning, prediction and automation tasks. Actually, intelligent machines are now capable to recognize and understand human instructions and fulfill their orders. In many ways, smart machines can outperform human in several ways such as workload handling, memory related tasks and processing powers required to analyze huge amount of data.

The following subsections provide examples for AI utilizations in manufacturing industry.

1.5.2.1 AI in Oil Production Management

Production procedures in the Oil and Gas industry require advanced technologies to achieve the desired processes automation as well as the different systems integration. These complicated requirements in such an important industry have been addressed by the introduction and implementation of a multilayer AI architecture, *connectivity layer*, *semantic layer* and *intelligent management layer*, to accomplish the significant automation of Oil production management [51].

The *connectivity layer* uses XML to handle all the information exchange activities between all applications and systems involved in this industry. Additionally, there is a dictionary that contains all the concepts and terms used for information communication from and to the various software and production systems in this specific industrial domain. This dictionary represents the *semantic layer*. Finally, the *management layer* uses intelligent multi-agent enabled systems to automate and computerize workflow processes and to control all production systems [51].

Testing the previous AI enabled architecture has demonstrated many advantages such as improved flexibility and efficiency as well as better ability to deal with different kinds of operational events and simulations. These benefits are acquired by the utilization of multi-agent systems in the management layer [51].

1.5.2.2 AI for the Reconfigurable Manufacturing Systems (RMS)

Reconfigurable Manufacturing Systems (RMS) that are enhanced with AI techniques offer several advantages to the manufacturing industry. Such manufacturing lines are capable to accommodate new processes in order to produce novel products with minimal cost and time required for the reconfiguration procedures. Thus, businesses would have the ability to apply any required changes in order to adapt to any anticipated market demands [52].

A typical example for such advancement in industrial lines is the *Reconfigurable Cellular Manufacturing Systems* (*RCMS*), which represent a manufacturing method that allows factories to use AI techniques to calculate the rearrangement and disposition of the work stations on the production floor as well as the movement of the products and workers in response to emerging trend in the market [53].

1.5.2.3 Hybrid AI System to Control Temperature in Steel Industry

In steel industry, controlling the temperature, which is needed to melt solid steel, for the proper period of time, is of major importance for the success of the melting process in order to guarantee that all hard pieces have melted as well as to avoid wasting unnecessary energy and time [54]. Traditionally, a single regression model, which is based on decision trees, is used to accomplish the temperature prediction and monitoring jobs. However, the model has some restrictions such as the limited accuracy when it comes to regression related tasks. This situation has embarked the need for smarter temperature prediction architecture that would make such procedure as accurate, economical and efficient as possible, by employing AI technologies [54].

Artificial Neural Networks (*ANNs*) are considered as one of the most important techniques in AI and can be simply defined as the computerized representation of how the human brain thinks and makes decisions [3]. They can be trained by using a set of historical examples in order to infer rules that can be used in the future in similar contexts and to solve related problems [3]. ANNs are capable of performing prediction tasks related to time and costs estimation issues with high accuracy because of their non-linear nature [54]. However, because of the complexity associated with their development, training and utilization, researchers have combined regression decision tress and Artificial Neural Networks (ANNs) in hybrid system that benefits from the advantages of both of those techniques, simplicity and accuracy respectively [54]. The system thus produced higher temperature prediction accuracy required for optimal steel melting process.

1.5.2.4 Machine Intelligence Enhanced Robots in Manufacturing

Industrial robots play a vital role in nowadays factories. Throughout the years they became smarter, faster and more productive. The new generations of robots employed in manufacturing are capable of performing many tasks that used to be only achievable by humans, but with higher accuracy and in larger volumes of production [55]. Moreover, advancements in AI research have enabled industrial robots to adapt to new variations in working environment in order not to interrupt manufacturing process. These robots are enhanced with a trial-and-use algorithm that allows them to learn from experiences encountered in the production floor. Consequently, those smart machines have some form of humans' cognitive ability that enables them to plan future actions based on the recent changes in the production line [56]. Accordingly, factories equipped with mobile robots use AI's *Genetic Algorithms* and *Ant Colony Algorithms* to plan the optimal paths that the robots have to go through to accomplish all the production tasks in the production environment as well as to avoid known and unfamiliar obstacles they might encounter in their way [55].

1.6 Machine Intelligence for Smarter Industries

The significance of machine intelligence stems from its ability to have intelligent machines that can simulate human behaviors at work environment as well as to analyze large amounts of complex data from multiple resources. It helps organizations to apply human-like intelligence in order to solve problems, detect frauds, improve customer relationship management related processes, and most importantly to have the ability to learn from data and experiences or what is called *Machine and Deep Learning* [57]. AI has several applications in the business world. These usages can be categorized into:

1. *cognitive science* as the research of emulating the mind and its processes within business settings in order to achieve better management such the intelligent data analysis, data mining, and expert systems,
2. *robotics* as the application of AI in industrial automation such as the automated manufacturing lines and transportations robots within factories, and
3. *natural interfaces* as the study of improving user's interactivity with the machines by utilizing easy to use touch screens that have the capabilities of gesture recognition as well as speech recognition, which allows users to interact with a system through spoken commands.

From all the discussion above about AI's role in industry, it can be concluded that decision makers in many organizations use AI-enhanced smart systems for activities related to management, planning and manufacturing operations. Similarly, AI has an influential role to support researchers in Big Data analysis, biological taxonomies and robotics [58].

1.7 Challenges for Machine Intelligence

The achieved progress in AI development and applications will continuously be tested with many challenges that affect its success to simulate humans' intelligence. Skeptics of AI always doubt its ability to solve problems, accomplish tasks, learn from experience [59], exhibit self-awareness, simulate human-like interactions [60] and finally, the ability to absorb and use knowledge [61]. Additionally, in the work of Doyle [62] and Shi [63] the authors have identified other big challenges that face the development of AI as well as its application in different industries and contexts. These challenges include AI ability to reflect motivation, purpose, imagination, consciousness, human memory [62] as well as rationality and introspective learning [63]. The last two are the elements that represent mental attitudes such as consistency and completeness as well as the ability to learn from failures and experiences [63]. Researchers have managed to make AI capable of tackling some of the previous difficulties; however, the way for complete self-awareness and human-like intelligence is still long.

Moreover, there are some common risks and mistakes that need to be aware of when specialists apply machine intelligence in industry [64]. First example of these is the lack of enough data for all development lifecycle: training, optimization, calibration, verification and validation. Second factor that needs to be considered is the difference between the training data while designing the intelligent system and the actual data while using it. Third aspect that is important to appreciate is to establish reasonable expectations that could be achieved by data mining and modeling. Additionally, the complexity accompanying AI implementation has to be considered in AI adoption project. Finally, it is vital to expect errors, thus, it is essential to set criteria for performance evaluation and to discover problems in the systems [64].

1.8 Case Studies

In this section we investigate some case studies about the implementation of Machine intelligence at work environments and we provide explanation about its role for the business success.

The first case study is about applying AI's Machine Learning techniques and algorithms to optimize the measures for *Power Usage Efficiency* (*PUE*), which are utilized in modern Data Centers (DCs) implemented at *Google Corporation* [65]. DCs in huge organizations, such as Google and Amazon, need to have the ability to handle the increasing growth of the generated data from various Internet enabled smart machines such as mobile devices and sensors. Additionally, those large data centers provide cloud computing services in a form of Software as a Service (SaaS) for other businesses in order to allow them save the costs of resources and operational manpower required for Big Data infrastructures. All these tasks are delivered by complex assembly of mechanical, electrical, electronic and software components and systems. Therefore, because of the increasing energy costs, there is a need for an approach that is capable of managing the power required to run such an intricate infrastructure efficiently [65].

Consequently, in 2014, the researchers at Google have applied multiple-layer artificial neural network that takes parameters such as workload, temperature of the working environment, and the number of the cooling towers as inputs to train the network. Then, it uses AI's processes and techniques such as *Random Initialization* and *Forward* and *Back Propagation* to achieve the accuracy required to predict the PUE as well as the cold water required from the cooling towers in different work environments and conditions in the DC. Such machine learning enhanced model offers opportunities for significant cost and carbon savings. Additionally, this architecture provides methods to simulate various configurations for the DC in order to be able to deal with future changes and demands [65].

Point of Attention Machine intelligence can be utilized in industry for more efficient work environment as well as power and resources utilizations. However, implementing machine learning algorithms requires several repetitions to train the implemented neural network and to find its optimal configurations.

The second case study is about utilizing intelligent robots in dynamic industrial environments. These work conditions are often characterized with constant changes, which causes many challenges for the robots working on the production floor [66]. Conventional *Automated Guided Vehicles* (*AGVs*), which are designed to deliver materials utilized in production from one location to another, move in an already specified path to reach the desired destination, unload, and go back to load again. However, due to limited navigation systems embedded in these early mobile robots, they are unable to adapt to any changes that might emerge in the production environment such as unforeseen obstacles. Thus, they only perform the pre-programmed manoeuvers. As a result, in case of any unpredicted error in the movement path, the whole production line would stop working until the obstacle is cleared [66].

Point of Attention Utilizing machine intelligence in industrial robots provides many opportunities for manufacturers. Intelligently automating tasks, such as, e.g., the delivery of raw materials and finished goods from the warehouses to the production lines and vice versa, would save a lot of resources and manpower required to accomplish such jobs. Thus, machine intelligence enhanced transportation robots would yield an improved and more efficient manufacturing process.

In 2008, the situation explained above made it imperative for a robotics producer, called *RMT*, to create autonomous mobile robots, called *ADAM*, that thanks to inventions in AI, are capable to govern their movement from the source to the destination and on the way back [66]. These smart materials transportation machines can autonomously adapt to changes and avoid obstacles in their pre-specified path [67]. The initial training is delivered by human operator who guides the *ADAM* through the factory allowing it to create a map of paths, walls and fixed machines. Then, the generated map is shared among the rest of the robots so they would have the same reference [66].

Taking the above issues into account, in the future, when a delivering mission is assigned to one of the robots, it can use the reference map to find the best path to deliver the goods. Additionally, since all of the robots on the factory's floor have the same reference map and continuously update their locations on it, they would have a better traffic management to avoid collisions during materials transportation [66].

1.9 Summary

The constantly changing market requirements have put additional challenges on the manufacturers to cope with the varying customers' demands. Thus, businesses as well as researchers are eager to utilize AI's techniques with the hope of achieving the desired level of Machine Intelligence in order to have the necessary flexibility that would allow manufacturing processes to adapt to emergent market circumstances. However, the complexity coupled with the implementation of AI's approaches have always been considered as one of the main reasons why industries refrain from adopting AI solutions. Therefore, it is imperative for both academic and professional communities to bridge the gap between researching in AI domain and its actual implementations in the industry in order to achieve the desired business objectives.

In this chapter, comprehensive descriptions for Artificial Intelligence (AI) and its various techniques have been provided. Moreover, descriptions of AI applications in two different business sectors have been discussed. The analysis has shown the importance of Machine Intelligence in a vital domain such as Healthcare. Additionally, it has pointed out the range of implementation areas in manufacturing sector. Nevertheless, proper research, management and experience are required to successfully understand the business domain as well as best AI's techniques that satisfy business requirements and enable machine intelligence.

Finally, the chapter has discussed two case studies, highlighting the significance and benefits associated with the adoption of AI in order to have smarter and more efficient businesses.

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Wearable Technologies

2

Abstract

This chapter introduces the reader to the basic terms and concepts of the wearable technology, its history, trends, implications and wide range of applications. Wearable technology is a rapidly evolving field and is expected to explode in the coming decade. It can be considered as a big umbrella term for any type of technological innovations that are used by wearing it on your body. Wearable computers are in fact connected devices always in the 'on' mode to make the appropriate measurements in real time. Furthermore, the use of assistive technology, e.g., by people with disabilities has also driven a continuing conversation about the use of tech to enhance human capabilities, for example, to track vulnerable people or using geo-location data for public health. Thus, wearable technology is a brand new world we are just beginning to uncover with never-ending opportunities and possibilities.

2.1 Introduction

Wearable computing, wearable computers, wearable gadgets, wearable tech or smart clothing, has recently moved from the realm of science fiction and military technology to being on the edge of everyday consumer technology [1–4].

It has become an interesting area of IT innovation that has received plenty of media attention over the past few years, but a reality check is necessary [6]. While some of these devices (e.g. Nike's FuelBand, Apple Watch or smart glasses to name a few) demonstrate the potential for wearable devices to change how we do daily routines or actually interact with information on a daily basis, many of these wearable technologies remain technologically limited. The good news, however, is that IT experts believe those limitations will be overcome in the near future as technology specialists work to address three main obstacles such as battery life problems, chipset limitations and design concerns [2, 4, 7, 8] (see Fig. 2.1). Global spending on wearable technology, which stood at $750 m in 2012, is expected to

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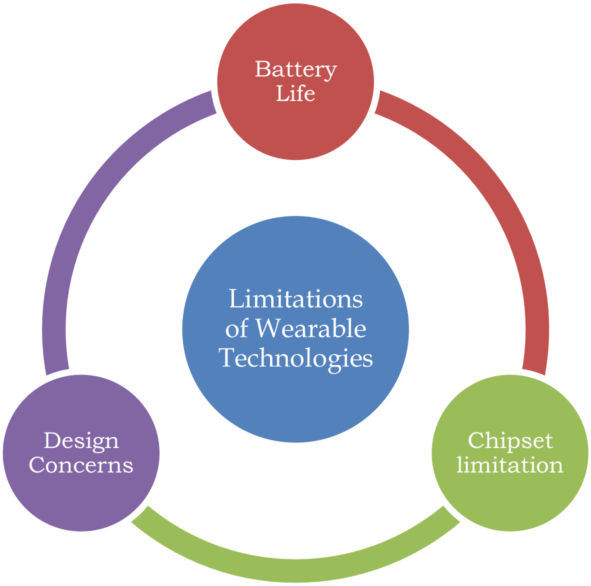


Fig. 2.1 Main obstacles for wearable technologies, adapted from [5]

reach $5.8 billion in 2018, according to Transparency Market Research [7]. So, what are the key areas of innovation that are helping to push developments in this fast-growing area?

2.2 Market Size and Outlook

Wearable Technology (WT) can now be considered as a massive global business [9–13]. From small start-up companies to major industrial companies, including Google, Samsung, Nike and Sony, everyone is seeing the opportunities for wearable systems to different degrees [14, 15]. Furthermore, online retail giant Amazon has also launched a dedicated wearable technology store in July 2014, confirming the importance of this product sector [16]. The Amazon store features over 100 different wearable devices currently, including products from big name brands and products from smaller emerging companies [17].

GfK [11], which is a trusted research group for relevant market and consumer information that enables its clients to make smarter decisions, has recently conducted an online interview with 1000 smartphone owners online in China, Germany, South Korea, the UK and the US to understand their usage of and attitudes towards ‘smartwatches’ and ‘activity trackers’. This section briefly summarizes the findings of GfK’s research, as it is insightful for the readers and researcher to note the current status of these two well-known wearables.

GfK's research highlights that WT consumers expect their devices to be controlled by touch rather than voice control. Accordingly, 67 % want to control their smartwatch with a touchscreen, 24 % say voice control and 8 % real buttons. Interestingly, nine out of ten also expect their smartwatch to run similar software as their smartphone, meaning that, they expect a similar experience on their smartwatches to that which they already have with their smartphones.

According to this report, when choosing a smartwatch, price, functionality and activity tracker functionality are considered as the most important criteria by 21 %, 14 % and 13 % respectively. Price is the number one criteria in all countries except China where it is not ranked in the top three. Instead, 'accuracy' is the most important criteria for Chinese consumers. Another notable difference is the emphasis placed on brand by respondents in China—15 % mentioned brand as being the most important criteria compared to just 8 % overall (see Fig. 2.2).

As to the question of, *which brand did you/would you buy a smartwatch from?*, results of the survey shows that tech brands are most favored by consumers. Almost two thirds (65 %) say they are most likely to buy a smartwatch from a tech brand, compared to 18 % who would choose a sportswear brand. These statistics show that amongst consumers there is a strong perception that wearables are first and foremost a technology purchase rather than a lifestyle accessory (Fig. 2.3).

Remarkably, when respondents were questioned on which functionalities were important for them when choosing a smartwatch, results revealed that smartwatch functionalities poorly understood by most consumers as activity tracking (29 %), taking phone calls (13 %) and telling the time (11 %) topped the list. The importance attached to activity tracking as functionality of a 'smartwatch' points to the fact that this is the function consumers are most able to understand, and there prioritize in any purchase decision. Evidently the full range of potential

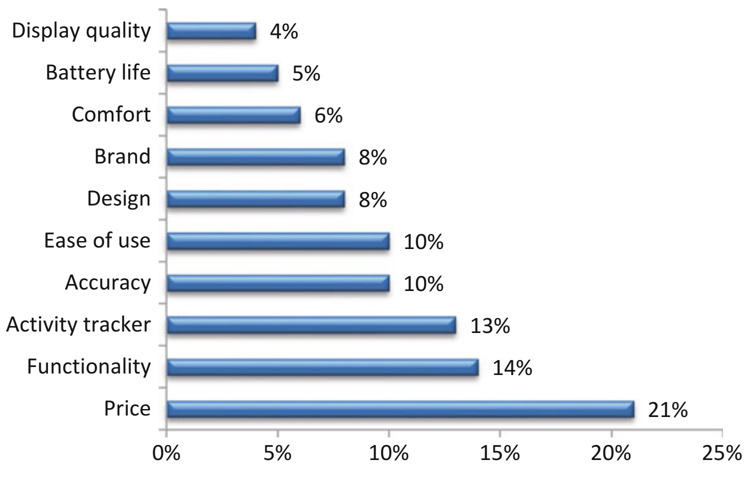


Fig. 2.2 Purchase criteria for WT devices, adapted from [10]

Fig. 2.3 Importance of brands in the smartwatch market

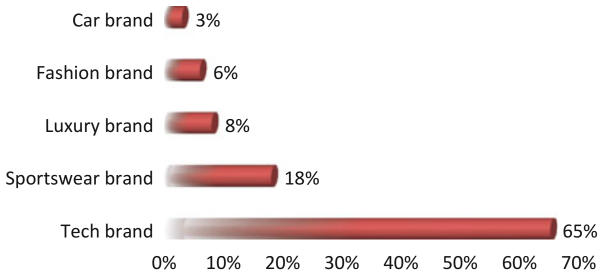
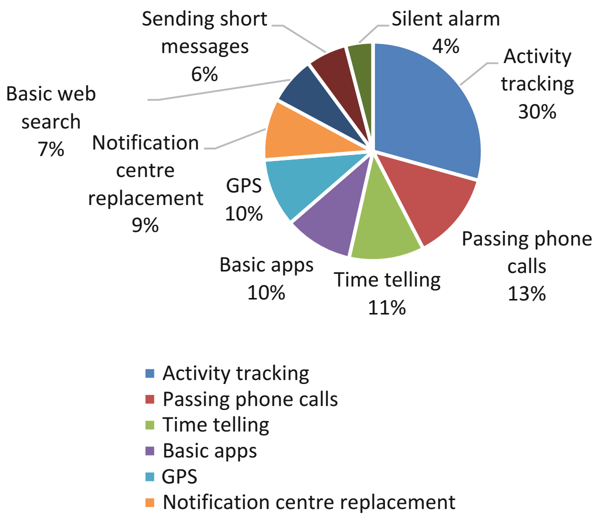


Fig. 2.4 Most important functionalities of smartwatches, adapted from [11]



applications of smartwatches and other wearables are, as yet, poorly understood (Fig. 2.4).

Tech analyst firm CCS Insight has also called on the consumer electronics industry to better articulate the advantages of smartwatches and wearable devices to the public if they are to survive the hype surrounding wearable technology [18]. The research included a survey of 4000 people in the UK, the US, China and Brazil on their views of wearable technology including usage patterns, awareness and current ownership. Taking a different perspective, CCS Insight's findings showed that a large number of respondents also indicated that measuring sporting activity was of less interest than tracking health and well-being factors such as sleep and heart rate. The results not only demonstrate a need for the industry to better communicate the benefits of smartwatches and wearables, but also to market their products in ways that suit consumers' preferences. Therefore, there is a clear need for manufacturers and software providers to work together to enhance consumers' understanding of other possibilities and functionalities offered by smartwatches if they are to achieve mainstream adoption [11].

Table 2.1 Percentage of luxury items with activity tracker by countries, adapted from [11]

Countries	Percentage of clothes/jewelry with activity tracker
USA	81
South Korea	72
Germany	73
China	71
UK	69

Table 2.2 Most relevant products for an integrated activity tracker, adapted from [11]

Type of products	Percentage
Bracelet	32
Shoes	29
Belt	15
T-shirts/shirts	11
Necklace	6
Trousers	4
Jacket	3
Ring	3
Underwear	3

Moreover, it is worth noting that 73 % of respondents in GfK's research also considered wearing clothes or jewelry with an integrated activity tracker which when divided by countries result as shown by Table 2.1.

And finally when respondents were asked on the type of product(s) they consider the most relevant to integrate an activity tracker bracelet, shoes and belt topped the list. The rest of categories were as shown in Table 2.2.

It is clear from the GFK research that there is huge potential for wearable technologies, both in terms of the size of this fast-growing market and the opportunities that this new technology offers to consumers. At the moment there is clearly a lack of understanding amongst consumers about the variety of applications for wearables and functionalities of such devices that can be improved through joint collaboration of WT device manufacturers and software developers via social media platforms.

2.3 Trends for Wearable Adoption

There are a number of technological and social trends that will play a crucial role in wearable adoption in the coming years. Below we summarize a number of these developments that will play a growing role in the wearable technology segment [14] (see also Fig. 2.5).

Advances in materials sciences will definitely be one of those critical areas, which may make new form factors and materials available for wearable computing and electronics. The University of Exeter in the U.K., for instance, recently

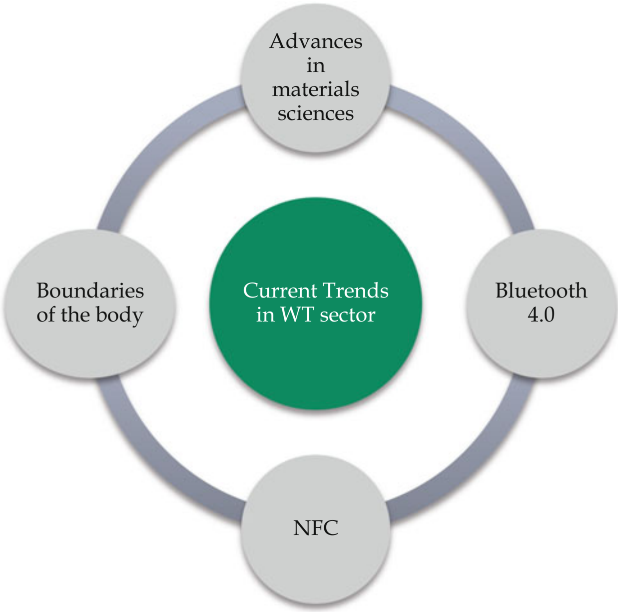


Fig. 2.5 Current trends in WT sector, adapted from [14]

announced the development of a new material called GraphExeter that can conduct electricity [14]. This material could be quite revolutionary in the Wearable Technology sector because the material is more flexible than the expensive materials currently used. Another key driver of wearables is the release of Bluetooth 4.0, which uses less power and can instantaneously pair with devices [14]. Bluetooth 4.0 is also a boost in the health market, due to connectivity with diverse medical devices and greater use with bracelets and watches, which are rapidly becoming important device platforms in the fitness and body-monitoring spaces. Furthermore, Near Field Communication (NFC) will also play a growing role in wearables too as it becomes a more commonplace technology used in mobile-money applications and services. There is already talk of embedding NFC technology in wearable devices so users can pay for different types of service from movie tickets, to subway tokens, to sporting events or simply a latte at Starbucks without even pulling out a card or phone, to name a few. This is provided consumers trust the technology to handle their financial transactions. Wearables are already causing a rethinking of the boundaries of the body and materials.

In her TED talk [14], Lucy McRae demonstrated some of the work Philips Electronics is researching and coined the term "*maybe tech*" for technologies that are not purely off or on the body and have the effect of blurring the boundaries of the body. Electronic tattoos that can conduct electricity and redefine the skin is an example of such efforts. In this way we can see how the body is becoming a platform or an API as nanotechnologies and computing converge in interesting ways.

2.4 Applications

Wearable technology is appealing to many consumers. In this section we summarize some of the current applications of wearable technologies.

2.4.1 Entertainment

2.4.1.1 Wearable Headsets

Workers in the digital age have become reliant on regularly checking their handheld devices to stay up-to-date with the surrounding environments, family and friends. Yet a new wave of technical innovation is likely to push knowledge right in front of faces. The most media-hyped example of wearable technology, Google Glass [19, 20] provides information on a head-mounted display and communicates with the Internet through natural voice commands. Glass can perform many of the tasks of a smartphone: it can take pictures, record video, give directions and send messages. At the lower-spec end of the spectrum, Oculus Rift [21–23], meanwhile, is a virtual reality (VR) head-mounted display. Thync is another company that creates wearable consumer products that make use of neuro-signaling to shift your state of mind by making on-demand shifts in energy, calm, or focus [8]. Thync in fact makes use of what they call 'Thync Vibes', which are intelligent waveforms delivered via neuro-signaling. These signals are targeted to specific neural pathways to achieve optimal results [24]. Augmented Reality (AR) offers a live view of a physical, real-world environment [25] whose elements are further enhanced by computer-generated sensory input such as sound, video, graphics or GPS data. The spread of smart mobile devices has led to rapid growth in AR with diverse from agriculture and architecture to education and medicine [13].

2.4.1.2 Smartwatches

Whereas smartphones has now become a normal part of life for millions of people globally, wearables are yet to achieve anywhere near this status for smartwatches. Computer-enabled wristwatches are not inherently new. Seiko and Casio developed data entry watches through the 1980s. What is new, however, is the ability to combine cheaper and smaller components in powerful and internet-enabled devices [7]. As far as buyers are concerned, smartwatches are not living up to their name. The widespread perception is that smartwatches are just activity trackers that tell the time. There is however the potential for wearable devices to overtake smartphones in terms of closer relationship between people and technology with innovations such as smartwatches, fitness armbands and data glasses that are generally used in conjunction with a smartphone [11].

2.4.1.3 Fitness Devices

Wearable technology has proved a popular adjunct to fitness routines—and it is not hard to see why. The potential to track and trace progress towards set fitness goals means individuals are prepared to invest money in technology that will provide real-time data of their health status. Nike's FuelBand, for example, is a smart pedometer that tracks steps, and provides motivational reminders and social connectivity. Fitbit, is another example, which offers a range of fitness tracking devices, and the minimalist Jawbone UP, which keeps interactivity to a minimum and does away with a screen [26]. As with smartwatches, reviews for fitness devices are mixed. Features on devices are limited, the initial cost is relatively high and connectivity with other technologies can be a concern, particularly when it comes to older or less popular smartphones.

2.4.2 Healthcare

Utilizing wearable technologies in healthcare sector brought forth many benefits for both patient and healthcare professionals (see Fig. 2.6) [25, 27]. Wearable technology could provide a platform to share patients medical data and to take necessary actions [5, 9, 10]. Thus, the availability and accessibility of patient's real time health records cold lead to better patient engagement with health and increased self-management in long term [28]. In addition to the remote access to the health data, wearable technology allows patients to keep an eye on their own health. Consequently, this could enable patients to make informed decisions on their own health.

Developments in smart healthcare technology are currently closely related to developments in smartwatches and fitness devices. Some of the companies pioneering developments in those areas already offer tools to monitor healthcare [9, 10, 29, 30]. Other firms are keen to gain a slice of a fast-growing sector [31]. Gaming specialist Nintendo recently announced its aim to target the

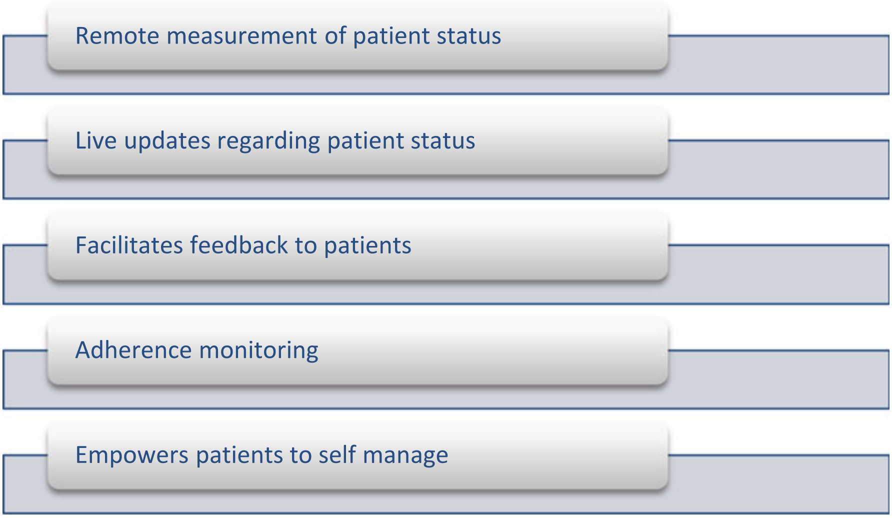


Fig. 2.6 Benefits of wearable technology in healthcare, adapted from [5]

healthcare market to help turn around its own economic fortunes [5, 10]. The advancement in the technology is likely to offer innovative solutions to some of the most healthcare's significant challenges. For instance, a recent innovative solution has been developed by the US-based company Proteus Digital Health to track patients' responses to medicine [5]. The device sends information wirelessly to the medical staff via pills stuffed with minuscule sensors. Electronic tattoos could be another solution as mentioned earlier. Other dedicated tools for conditions like diabetes are beginning to surface as well.

In the US the Food and Drug Administration (FDA) has recently approved Medtronic's MiniMed 530G, a wearable, artificial pancreas that monitors blood glucose levels and injects insulin to a defined threshold. Johnson and Johnson is also creating Animas, an external unit that monitors insulin levels automatically [13]. Remote monitoring of patients using wearable sensing technology may also mitigate the problems associated with access to healthcare.

2.5 Wearable Technology and Big Data

Over the past few years, healthcare research and development has relied on big data to advance medical science and create better diagnostics and drugs. Big data wearables capitalize on two huge trends: 'big data' and 'wearable technology' [32]. The fact that many well-known companies such as Google, Apple, Microsoft and a host of fitness-device manufacturers are making significant investments in this area reveals that we are on the verge of wearables becoming mainstream devices in the coming years [14]. With the health and fitness gadgets currently taking the lead in this sector, wearables will begin to occupy a growing role in the mobile-health sector, and data analytics as well as big data will become important services linked to their growth [14]. For example, Wearable technology such as the above-mentioned Google Glass, Nike+ FuelBand and the reported Apple Watch will not only enhance consumers' lives, but will also provide a new source of commercially exploitable data [15].

Call it wearable tech, the Internet of Things (IoT), or the quantified self—all terms reflecting a reality in which we collect as much data about our personal lives as we do (or should) about our sales figures. And what we do with that data could profoundly impact workplace culture and productivity [33]. The term 'Internet of Things (IoT)' usually refers to the interconnection of uniquely identifiable computing devices embedded in a whole host of things around you, such as heart monitoring implants, cars, thermostats, washing machines, etc. This interconnection of chips, means that practically everything will be connected to the Internet. Gartner predicts that there will be nearly 26 billion devices connected to the Internet by 2020 [26].

Another category closely related to wearable tech is the trend referred to as *quantified self-life*. As mentioned above, the computers that we wear make different types of measurements and analyze data in real time. Consequently, we can keep track of just about anything such as how many calories we've burned in s specific time frame, how many steps we've walked, for how many hours we slept, how we slept, what is our blood pressure, respiratory rate, etc. Since all these devices are connected, we can share all the information to be analyzed by other parties or in our own applications. The amount of generated information is so vast that experts are talking about a shift from big data to my data [12].

The numerous amounts of data collected via wearable devices could represent an issue of concern. For instance, health and fitness gadgets can capture sensitive data about users' health and make them available to the tech vendor via cloud technologies. Moreover, the captured data might be shared with third parties for 'big data' profiling. To comply with the law, wearable device manufacturers and suppliers will need to consider a multitude of data protection, privacy and security issues. These then need to be dealt with properly at design stage, at the point of data capture and once the data has been collected [34]. In other words, more collaboration between researchers in IT and medical fields as well as data scientist is highly essential at the design stage. The result of this collaboration would be a complete proper system including global networked computing environment of smart sensors, software, data centers and devises.

2.6 Challenges of Wearable Technology

Since 2008, wearable technology that can cover a broad range from measuring your heart rate to curating music based on your mood has been advertised as the next big moment in consumer electronics [6]. Nevertheless, the wearable technology market is not without its challenges. WT devices are typically divided into three categories: complex devices such as fitness trackers; smart accessories such as smartwatches, defined by their ability to run third-party applications; and fully autonomous smart wearables that connect directly to the Internet, such as Google's Glass headset (Fig. 2.7). It is believed that WT devices will reach 19 million units this year alone which will be more than triple last year's sales [6].

According to the study, a large segment of consumers (i.e. about 75 %) are generally aware of wearable technology gadgets however a very small portion of consumers (i.e. about 9 %) actually have any interest in buying and wearing it and even a smaller portion of 2 % admitted to essentially owning a wearable tech device, most of which consist of fitness trackers and smartwatches [6]. The question is why the number of adopters is small? According to [35] the research director of the US based benchmarking and education firm L2, Colin Gilbert, 'style' is not the only missing piece to the WT puzzle, but it's something to look forward to. More than half of the report's respondents want devices that feel more like jewelry while 62 % would like more than wrist-worn devices [6]. Nonetheless, the "cool" factor isn't the only issue. Security and privacy, particularly around the management of consumer data, remain a major issue as the tech industry seeks to bring more of our body parts online.

According to a report by [36] there are reasons many wearable devices fail to achieve long-term user engagement. Many consumers see obstacles to purchasing

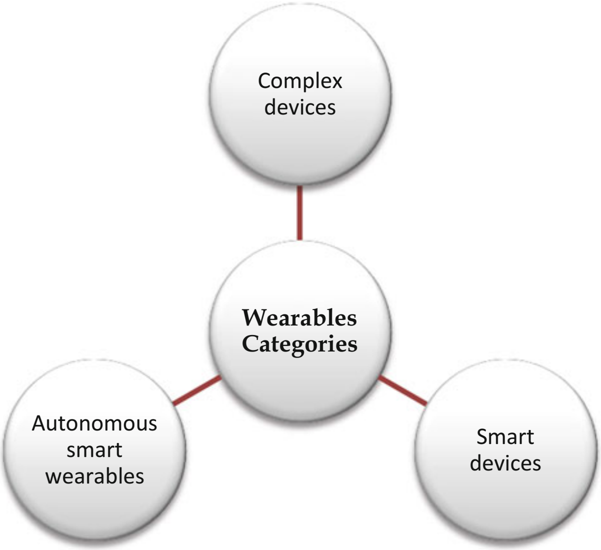


Fig. 2.7 Categories of wearable technology devices, adapted from [5]

wearable devices including the expense of devices and security and privacy of data, the look, comfort and health risks being other concerns among users [5]. As reported by Endeavour Partners while one in ten American adults now own an activity tracker, one third of users stop using the device within 6 months of receiving it [36]. According to this report, many wearable devices fail to achieve long-term user engagement due to a number of flaws [36]:

- They are easy to lose
- They break
- They are not waterproof
- They are a pain to sync with your smartphone
- The battery doesn't last long enough
- They are ugly
- They are uncomfortable to wear
- They provide no material benefit

Endeavour Partners believes that wearable technology companies need to really focus on real needs of consumers and develop devices that become an integral part of their day-to-day life. Devices need to address a wider and more interesting set of consumer problems than the existing designs.

As for these issues, Fig. 2.8 shows the main challenges of Wearable technology. Each challenge is now explained briefly but 'data security and privacy' due to their importance is explored in more detail.

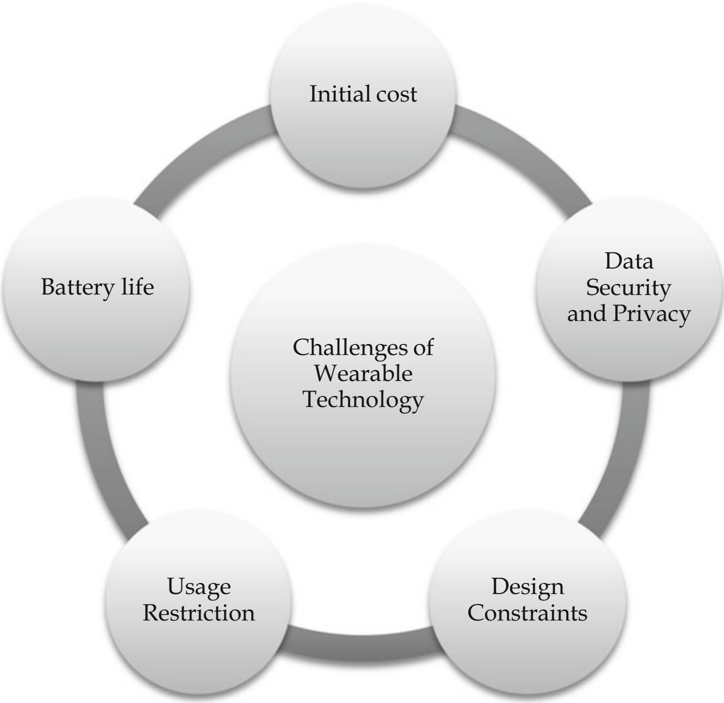


Fig. 2.8 Challenges of wearable technology

2.6.1 Design Constraints

The design of wearable technology is an important issue for the end users. In fact, most consumers use wearable accessories such as watches, jewelry and wristbands to make a statement about their personal identity and their fashion trend. Currently, however, most wearable device manufacturers give less consideration to the design of the WTs compared to the technology aspect. For instance, most of smartwatches use components that are designed for smartphones and thus they are bulkier than ordinary watches.

One of the major challenges in the Smart Wearable Technology market is the design constraint of wearable devices as most consumers use normal wearable accessories such as watches, jewelry and wristbands to make a statement about their personal identity. In other words the wearable item reflects the fashion trend of the users. Currently, however, most smart wearable device manufacturers have focused on technology aspect of WTs rather than on design. For instance, most of the smartwatches run on processors and components that are designed for smartphones so they are bulkier than a normal watch.

2.6.2 High Power Consumption

Another main challenge that may attribute to lack of usage and adoption of the WTs is high power consumption. This excessive power consumption is attributed to the fact that most wearable devices are supported with built-in features such as Wi-Fi, GPS and other technologies. As a result, the current battery life of wearable devices does not last for long. For instance, in case of intensive usage, the Google Glass battery lasts only for 4–8 h. So the issue of short battery life if not tackled may hinder the expected growth prospects of the market during the forecast period.

2.6.3 High Initial Cost and Usage Restrictions

The high cost of smart wearable devices is another challenge that is expected to limit the boom in the WTs market. Currently, most of wearable devices are launched in premium and luxurious product categories. Undoubtedly, this affects the affordability and therefore results in a very low mass adoption of wearable devices. Furthermore, though wearable technology hasn't been around for long, it has been on many companies' radars for a while. Thus, the possibilities in terms of functioning and applications are potentially endless for wearable technology. But while this is great for consumers, it isn't the best news for businesses that require strict laws and high security to operate. So far, wearable technology has been banned in casinos, movie theatres, and even some restaurants have disallowed their patrons to adorn wearables [37].

2.6.4 Lack of Data Privacy and Security

As WT devices grow in popularity, so do concerns over security and privacy of data. In this section we list some of these concerns. Most wearable devices are small in size, but they are able to store a huge amount of data. The small size of these devices means that the chance of them being lost or misplaced is high. Since they store a large amount of sensitive information, smart wearable devices can be disruptive for users. Wearable devices use GPS navigation systems to receive location-based information. Sometimes, users have to share their location to obtain certain information. For instance, Google Glass users have to share their location while checking-in at Foursquare, which is stored in its database. This information can be retrieved and used by advertisers as well. Moreover, the data about a subscriber's location is owned and controlled by the respective network operators, which includes mobile carriers and mobile content providers. Despite available legal frameworks [5, 10, 26, 37], WTs end-users are concerned about the intrusion on their privacy by other stakeholders. Furthermore, data privacy and security is considered as one of the main concerns for wearable technologies. No difference to computers and smartphones, wearable devices create an enormous volume of personal and detailed data that is extremely appealing to cybercriminals

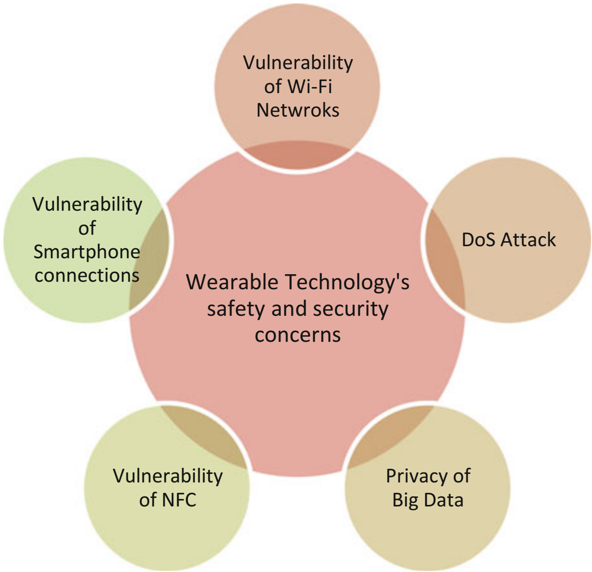


Fig. 2.9 Wearable technology safety and security concerns

[38]. Without the proper security, wearable devices with cameras, like Google Glass, could be hacked allowing the cybercriminal to gain information about where the user is, what they are doing, and who they are with [38, 39]. Even the data generated by activity trackers that use GPS could be used by cybercriminals to determine where the user lives and when they leave the home, office etc. The connection between many wearable devices and a smartphone is also another potential point that hackers can attack. For instance, Apple watch can be connected to other apple products such as iPhone, iPad and other Apple devices. With this in mind, such connection will definitely become a potential attack vector [39] (see Fig. 2.9).

Another issue with wearable technology is data ownership. Wearable devices like Fitbit and Jawbone have the ability to acquire huge volumes of data but the question remains as to who actually owns the data generated. The Federal Trade Commission in the US published findings of an investigation on 12 different health app and the result was that these apps transmitted information to 76 different third-parties, including consumer health metrics [30]. In order to overcome these safety and security concerns associated with wearable technology, devices need to comply with the necessary technology regulatory standards with most wearable device manufactures relying on the International Electro technical Commission's International Standards to operate reliably and safely. That in mind, we briefly take a look at how we can expect to be attacked in this sector [39].

2.6.4.1 Vulnerability of Google Glass on Public Wi-Fi

As for the vulnerability of Google Glass on public Wi-Fi, the well-known security firm Kaspersky decided to run a few tests on the technology to see how it performed on public Wi-Fi access points. The result showed that the security firm could determine what could and couldn't be seen from a user's activity. While almost all the traffic from Glass was encrypted, enough however was left in plain text to inform hackers what sites they had visited.

2.6.4.2 Denial-of-Service Attacks May Affect Doctors' Tools

The potential advantages wearable devices offer to improve medical technology have been one of the big selling points of the technology in the public sector. Doctors, for example, have long been using computers to aid the medical process, and wearables seem like a perfect fit. Unfortunately reliance on wearables opens up worrisome possibilities. As Trend Micro's well known senior threat researcher David Sancho wrote in a blog: "A simple Denial-of-Service (DoS) attack could prevent a doctor from operating on a patient or prevent a law enforcement agent from acquiring input data to catch criminals" [39].

2.6.4.3 Privacy Is at Risk as Wearables Collect Data

Consumers are now used to their smartphones doing research on them and wearable tech offers even more chances to take notes on our behavior, which is potentially useful but also potentially dangerous. Hackers have already become skilled at summarizing, and this trend is only set to get worse. Fitness bands, for instance, that monitor and capture information about our movement using GPS, can provide a malicious user with details about our daily routines and patterns, as well as our current location.

2.6.4.4 Digital Pickpocketing Is Likely to Rise

With the rise of contactless payments, thanks to near field communication (NFC), the security industry has warned about the risks to the user of having money stolen from them (their cards) in what is sometimes called "*digital pickpocketing*". One form can be used by converting a mobile into a radio frequency identification (RFID) scanner that once set up, the user can seek out payment cards with RFID chips, before exploiting them to steal money from unaware victims [39].

2.6.4.5 Smartphone Connections Could Be Exploited

It is very likely that at some point Apple Watch may become self-sustaining, but right now they need to be tied to an iPhone in order to work—this is also true for other tech companies such as Samsung. That connection also creates an additional point that hackers can attack. Ken Westin, security analyst at Tripwire for instance explains that the device connects to iPhones and other iDevices, so that connection will definitely become a potential attack vector [39].

2.7 Case Studies

In this section, a number of small-medium enterprises that have developed wearable technology solutions are outlined in a case study format, representing market and emerging trends.

In the first case considered, Charles Settles is a Product Analyst at Technology Advice (TA), a Tennessee-based company that provides unprejudiced research on business technology [40]. He believes that there are a number of exciting business applications for wearable technology on the horizon. He explains that in TA they educate, advise, and connect businesses with software solutions and one of the areas that increasingly our customers are asking for is related to software that will allow them to integrate wearable devices into their operations in the healthcare realm, which is one of the most promising areas for wearable technology. drChrono is one of the companies that experimenting with a Google Glass-based electronic health records solution that allows physicians to maintain eye contact with their patient while doing the routine procedures such as taking notes, recording orders, and even referencing patient history. This could therefore solve one of the biggest complaints made by providers and patients that is the documentation process for electronic health records kills the physician/patient relationship. Google Glass includes a camera, display, touchpad, battery and microphone, all built into display frames. Google Glass is controlled by a microphone and touchpad on one arm of the frame and the device syncs to Google Drive, and has in-built Bluetooth and Wi-Fi. Smart glasses thus may help healthcare professionals to work more efficiently allowing doctors to access healthcare records without having to break eye contact with the patient.

Point of Attention Wearable technologies such as Google's head-mounted glass can help physicians to overcome the challenges of the documentation process for electronic health records that kills the physician/patient relationship. It could even allow surgeons in the sterile environment of an operating room to document findings in a patient's medical notes and in real-time share this data with colleagues.

The increasingly usage of wearable devices by lay consumers may present a great opportunity for physicians to provide these devices to particularly at risk patients. Being able to monitor a patient's vitals in real-time without requiring a hospital stay could be a game-changer for heart patients, chronic disease sufferers, and their physicians.

In the second considered case scenario, it is noteworthy also to brief the viewpoint on the body worn camera by Tiffany Wang is the Vice President of Sales for Wolfcom Enterprises, a manufacturer of body worn cameras for Law Enforcement and consumers. According to her, businesses will be investing in various applications of WTs to expand their applicability. For instance, body worn cameras are becoming smaller and lighter. Already in use by police agencies across different countries and particularly US, these cameras are worn by police officers to record interaction with the public. This has resulted in a reduction of complaints and lawsuits saving cities across America millions of taxpayer dollars in payouts from false claims. Body cameras will be the next wearable technology and one southland company is betting on it.

To widen its applicability, body cameras manufactured by Wolfcom are designed to be light and wearable. Moreover, the founders stated that there is incredible opportunity to provide their cameras to a wide group including doctors, attorneys, social workers, process servers, and just about anyone exposed to the possibility of frivolous lawsuits. The camera, Wolfcom Vision', is characterized by high recording and storage capacity; store up to 36 h of video, take up to 56,000 photos and record up to 360 h of audio. Amazingly, the camera is integrated into a lightweight unit that is smaller than a business card and clips right onto either a shirt or belt.

Point of Attention At a flick of a switch, business professionals can now record interactions with their clients, monitor employee interactions with customers or record their everyday activities. The recorded videos can then be used to settle disputes and allegations as well as be used for customer service training.

External headset cameras is an addition to the 'Wolfcom Vision' which makes it perfect for those requiring Point of View (POV) recording such as a building inspector who needs to record where his eyes are looking and where chest mounted body cameras cannot see or record such as ceilings, pipes, floors, blueprints, etc. Therefore, body worn cameras are a promising technology for businesses and they will be here to stay.

2.8 Summary

This chapter has discussed wearable technology as a trend for business innovation. Once seen as a novelty, the area is ever expanding, with new devices been launched practically every week if not every few days. Wearable technology is per se, an umbrella term, that covers all types of technologies that are worn on the body, from sensors that measure fitness to accessories such as smartwatches, to fully autonomous smart wearable devices that connect directly to the internet, such as Google's Glass headset.

There are many advantages of using wearable devices. The advantages include measuring and monitoring physiological and biomechanical systems of the body as well body movement. In addition, wearable devices allow users or external parties to capture data on individuals' behaviour and to monitor their health and fitness.

Besides that, wearable devices enhance individuals' engagement with the external environment. Such advantages are not limited to healthcare professionals and patients rather they appeal to other stakeholders such as athletes and their trainers as well as the average consumer. According to Global Web Index [2], 64 % of global internet users aged 16–64 have worn a piece of wearable technology already, or are keen to do so in the future.

Many wearable devices are wireless and this feature, combined with the small size of many of the sensors used, makes them easily integrated into wearable systems. Sensors have so far been integrated into garments, hats, wristbands, socks, shoes, eyeglasses and other devices such as wristwatches and headphones making them truly wearable [9]. Advances in sensor technology, microelectronics, telecommunication, and data analysis techniques have also been attributed to the huge increase in wearable technology. According to Robert Scoble, startup liaison officer at Rackspace Inc., the transformation in wearable technology is being fuelled by cloud computing. "It allows the data generated by wearable devices to be captured, analysed and made readily accessible whenever users need it" [41]. Johan Svanberg, Senior Analyst with Berg Insight says, "A perfect storm of innovation within low power wireless connectivity, sensor technology, big data, cloud services, voice user interfaces and mobile computing power is coming together and paves the way for connected wearable technology," [1].

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