DT QUANTUM MODEL

Calculate and evaluate digital transformation process: a quantitative approach

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FOREWORD

I have been working for years in the art of developing and analyzing metrics. But my interest has focused not only in constructing them, but in analyzing them through time-series data visualizations, in order to look for changes, variations and disruptions.

During my research in defining new metrics to calculate efficiency, productivity, profitability, Return Over the Investment (ROI) or impact of projects, processes and investments, I concluded that, in management, there must be a quantitative way to measure the success or fail of a project. If there is no way to measure results in a quantitative way, there could be something wrong on a project's design. Why? Because a project should has a numeric procedure to justify itselt in front of managerial levels or decisions makers. This is the base concept of Diagnostic Analytics: analyze what happened in the past to try to explain the present and then try to predict the future in the most accurate manner possible.

The adoption of Digital Transformation (DT) processes in organizations brings along, sometimes, massive financial investments and almost an internal-operational revolution. Such transformation processes, usually, are executed in the form of projects. Companies define costs, operational necessities, organizational-culture issues, team-work initiatives and, finally, decide, according to such variables, the right time to begin its execution.

The DT of an organization is a process in which new digital technologies are inserted to improve the productivity and efficiency of operational processes. Usually, DT initiatives pursue total or parcial automation of processes. This progression in an entity, either public or private, must be a process in which the managerial authorities who lead it should be capable to calculate, not only its evolution, but its results in time.

Once the digital transformation process (project) initiates and the organization begins the journey, it is absolutely crucial to follow up its execution in time, but not only in terms of the initial investment (ROI), but in intensity of the process and its correspondent potential savings.

Thus, the fact of having a single numeric coefficient to measure DT's intensity in time is decisive for executives, and even more relevant is the circumstance of calculating potential savings in future DT investments due to real-results-experience in previous DT's projects.

Precisely, this capability to measure, in a quantitative way, its results in time, is the main core of its success: build the capacity to show numeric metrics and coefficients that proof the benefits obtained after the implementation of such process.
The DT Quantum Model proposes the development of two coefficients to measure and evaluate the digital transformation process of an organization. It proposes, in a first approach, the development of two coefficients; they are based on the analysis of the evolution of historic-based data series, due to certain disruptions in the quantity of transactions (manual tasks), in a certain period of time, of determined operational processes before and after the insertion of digital technologies. It suggests the fact that such disruptions can be evaluated in a immediate and in a sustained term, since the specific moment of the insertion of an automation initiave. Two coefficients are proposed: the Immediate Digital Transformation Coefficient (IDTC), that measures the immediate disruption from the highest value registered to the immediate lower one (quantity of manual operations in a historic-based data series). The Sustained Digital Transformation Coefficient (SDTC) measures the sustained disruption from the highest value registered to the lowest one (final value of the dataset analyzed). These disruptions should reflect, if they show a positive result (a reduction in the quantity of maual tasks in a certain operative process), a DT process due to the insertion of digital technologies.

In a second approach, such model proposes, based on the result of the mentioned coefficients, the possibility to estimate its intensity.

In a third approach, it proposes, also based in the results of the coefficients, potential-estimated savings for the organization in some key areas for future DT projects.

ACKNOWLEDGEMENTS

To God, by whom all things are made.

To my lovely wife Ana and my kids Felipe and Lucia. Always beside me. Your sacrifice has made this book possible.

To mom and dad, your advices and wisdom will ever resound in my ears and your legacy and sacrifice will always flow through our veins…

To all those brave, determined and corageous trailblazers, pioneers and innovators worldwide that, even against the greatest of odds, have decided to take a step forward and adopt different types of Digital Transformation processes in their organizations. You are true heroes. The world needs you to learn how to thrive through time.

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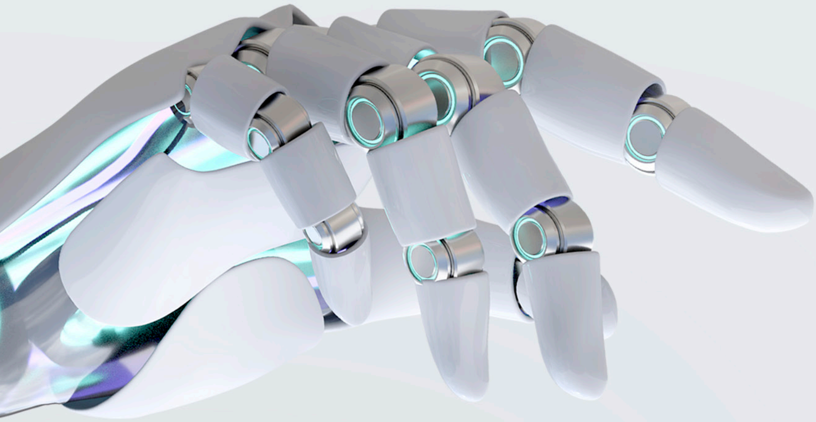


INTRODUCTION

Digital Transformation (DT) is everywhere. It has touched and involved almost every activity of human life. It has been related with lots of different types of industries: medical, engineering, high-tec, banking, agriculture, mining, biology, chemistry, investments, academic, statistics, manufacturing, public and private sectors, law firms, Enteprise Content Management, energy, telecommunications, transportation, construction, sports, executive education, etc. There is a single reason of its appearance in stage: competitiveness.

As soon as the imperative desire to become more competitive has appeared, there is a force that has pushed people and organizations to reinvent themselves, to find new ways to do things, to cut costs and operational response-times and to increase efficiency. All of that with one main objective in mind: getting a better position in market in face of customers (private sector) or users (public sector), and beside competitors, as well.

The main core of such tasks to increase productivity by cutting costs and expenses, lyes in the fact that manual tasks must be replaced by automatic work, generating important financial, labour, operational, digital bandwidth and time savings. Manual duties take the form of industrial, administrative, documental or finance processes, that would be replaced by new technologies in the way of new machines, computers, informatic systems, robots, apps, digital signatures, specialized software, enterprise content management platforms, records management, DevOps structures, etc.

The concept of DT has been a focus of tons of research projects worldwide, usually, related with the environment of the person or organization that executes such research. Thus, its definition and vision-pattern depends, in an important percentage, of the operational, organizational, legal and even cultural atmosphere or situation that surrounds the researcher in a specific period of time.

Ismail, Khater and Zaki (2017), indicate that “the digital transformation phenomenon has been explored widely in different academic domains, resulting in a crude overview of the field” (1). They defined that a complete “business transformation includes a change in four key areas: Re-engineering, Restructuring, Renewing and Regeneration” (1). Additionally, they refer to the fact that “such process has been analyzed in several perspectives: individual, company/institutional, network, industry/ecosystem, social/economic and era” (1).

Hence, according to the autors mentioned in the above paragraph, there are as much definitions as perspectives of digital transformation processes exists in market. What is absolutely clear, is that “all of the above-mentioned types of transformation create tensions in norms and behaviors between old competencies and present and future challenges” (1).

Precisely, such tensions and forces between the old manners and the new ones (behaviors, conducts, processes, culture) have generated an incredibly fierce battle in organizations recently. People and organizations worldwide, in a daily basis, face ferocious forces in face of the insertion of new technologies. One force does not want to change and the other one wants to move on to innovate in new ways to do things.

Little by little, day by day, minute by minute, the “new manners side” seems to be winning such battle during the last years. Results are clear and visible in the field: new technologies have occupied the actual world’s landscape shaping a totally brand-new one.

Therefore, change is DT’s heart. Consequently, digital transformation processes are flowing through organization’s veins at a speed that seems not to decline. Accordingly to such phenomenon, its speed is accelerating more and more and appears not to stop.

Westerman, Bonnet and McAfee (2014), express that “Digital Transformation — the use of technology to radically improve performance or reach of enterprises — is a hot topic for companies across the globe. Executives in all industries are using digital advances such as analytics, mobility, social media and smart embedded devices as well as improving their use of traditional technologies to change customer relationships, internal processes and value propositions. Other executives, seeing how fast digital technology disrupted media industries in the past decade, know they need to pay attention to changes in their industries now”. (2).

At this point, due to the mentioned arguments so far, digital transformation refers to a change process. Alekseevna and Yakovlena (2017) mention that “Digital Transformation (digitalization) of economy is the global change of economic relationships, which is characterized as moving of these relationships into the cyber-physical world. It includes transfer of objects and subjects of those relationships conducted by conceptually new entities that have never existed before. For example, new jobs, new products (stickers in social networks, apps making decision for people about what to wear, where to go, selection of fitness exercises, places for saving data – cloud storage, etc.)" (3).

Thus, another relevant element is the fact that a lot of DT processes in organizations have been transformed into an investment project. How much money is dedicated to buy new technological equipment, how much money is necessary to develop new software, how many people is necessary to execute the brand-new workforce processes, how large is the budget focused in Research & Development (R&D)… those are some questions managers and decision makers have been asking themselves every day actually. However, from the starting point when organizations begin their journey of transformation and automation, how do managers know how are they doing with it? How to know if they are moving through the correct track? How to know if such process is generating the expected impact? How do they know if such process has been intense or weak? How do they monitor its execution? How do they know how to defend it in front of the Board of Directors? How do they generate and evaluate quantitative results?

Matt, Hess and Benlian (2015) indicate that "in recent years, firms in almost all industries have conducted a number of initiatives to explore new digital technologies and to exploit their benefits. This frequently involves transformations of key business operations that affects products and processes, as well as organizational structures and management concepts. Companies need to establish management practices to govern these complex transformations. An important approach is to formulate a digital transformation strategy that serves as a central concept to integrate the entire coordination, prioritization, and implementation of digital transformations within a firm. The exploitation and integration of digital technologies often affect large parts of companies and even go beyond their borders, by impacting products, business processes, sales channels, and supply chains. Potential benefits of digitization are manifold and include increases in sales or productivity, innovations in value creation" (4).

Furthermore, the ability to express, in a quantitative way, the results, impact or consequences of digital transformation process within an organization must be a priority in the task-portfolios of managerial authorities. Not only to defend the correct and convenient implementation of related projects facing boards of directors, but to justify future-potential investments in new technologies, these kind of metrics are crucial to assure, in the highest-possible percentage, the sustainability and growth of these initatives.

Kane, Palmer, Nguyen-Phillips, Kiron and Buckely (2015) express that “in general terms, organizations and specialized consulting firms have been using, to approach into a calculation of the digital transformation process, a wide variety of Key Performance Indicators (KPI) and some other quantitative and qualitative metrics. Those indicators cover extensive operational areas of organizations and are used to keep track of its progress in time. Only 15% of respondents in a survey of 4,300 managers, executives, and analysts said their organizations have a clear and coherent digital strategy for moving beyond an early stage of digital maturity” (5).

Hence, there is a large inventory of metrics that attempt to evaluate the progress, impact or results of the digital transformation process in an organization. Based on my experience, such metrics must be conclusive, quantitative and systematical coefficients that summarises, in one or two numbers, such elements. They must be metrics that really reflect the process itself and its intensity, that really give a clear result of its impact. They must be concrete numbers that synthesize simply its results in time. In addition, they must generate inputs to perform savings estimations due to real-quantitative results of past DT projects.

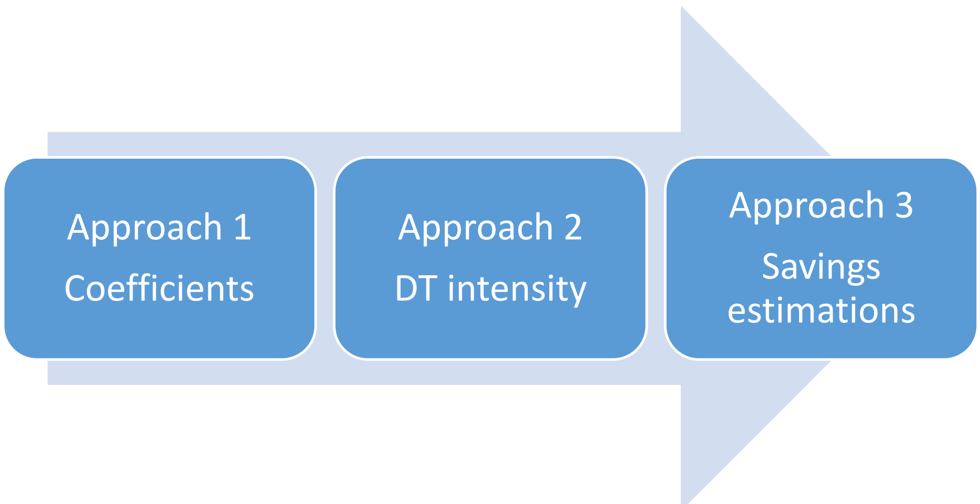
One approach to calculate the quantitative impact or results of DT processes in time, is related with the evaluation of disruptions that the insertion of digital technologies produces in manual operational processes in organizations. In a certain moment in time, if a digital technology is inserted in an operational-manual process (in order to substitute manual operations), a decrease in the quantity of manual tasks in such process is expected. In such specific moment, due to that change, a disruption is generated and, consequently, a percent variation can be calculated. Precisely, such numeric disruption is the core of the methodology proposed in this book.

DT Quantum Model proposes the development of two coefficients to calculate and evaluate the digital transformation process of an organization; they are based on the analysis of the evolution of historic-based data series, due to certain disruptions in the quantity of manual transactions, in a certain period of time, of determined operational processes after the insertion of digital technologies (structured data). In addition, it proposes the fact that such disruptions can be evaluated in a immediate and in a sustained term, since the specific moment of the insertion of an automation initiave. Finally, based on coefficient’s results, it proposes an estimation to calculate potential savings for organizations in various areas.

In this specific case, DT Quantum Model proposes a quantitative approach under the premise that it works with Quantitative Data, whose definition consists in structured data which variables are numbers that could be counted.

Two coefficients are proposed: the Immediate Digital Transformation Coefficient (IDTC), that measures the immediate disruption from the highest value registered to the immediate lower one (quantity of manual operations in a historic-based data series) after the proper insertion of new technology. The Sustained Digital Transformation Coefficient (SDTC) measures the sustained disruption from the highest value registered to the lowest one in the dataset analyzed. These disruptions reflect a digital transformation due to the insertion of digital technologies.

Therefore, the following image summarises DT Quantum Model's approaches:



The usage of the proposed development would provide decision-makers and managerial authorities of any organization, the capacity to evaluate the digital transformation process in time, with the main purpose of monitoring such process to take timely decisions to improve or enlarge its impact, and to justify potential financial expenditures on it.

Finally, in order to illustrate model´s theory, a simulated business case is developed and explained.

CHAPTER 1:

DIGITAL TRANSFORMATION: MAIN IDEAS

Digital Transformation: an approach to its concept

Hoberg, Krcmar, Oswald and Welz (2015), said that “Digital Transformation is a hot topic for debate at the moment and is well-suited to determine the business agenda of companies worldwide in the foreseeable future. The increasing digitization of our private, professional, and public life is commonly referred to as a disruptive process that is fundamentally changing the way companies compete, create value, and engage with their business partners and customers”. (6).

Also, Henriette, Feki, Boughzala (2016) mentioned that the definition of DT goes much more beyond a change in operational processes. “The digital transformation, otherwise called “digitalization”, is defined today rarely in the literature. Our literature review shows that the digital transformation is defined as a social phenomenon, or cultural evolution or creation of business model, indeed, it is perceived as a fundamental transition of society, driven by generations called “digital”. For this, we propose defining the digital transformation as “a disruptive or incremental change process. It starts with the adoption and use of digital technologies, then evolving into an implicit holistic transformation of an organization, or deliberate to pursue value creation” (7).

In another point of view, Andersson, Movin, Mähring, Teigland and Wennberg (2018) focused on the fact that DT generates disruptions. “Digitalization disrupts markets. Changes in power and structures in a fast-paced environment demand strategic and insightful change. A change leader must act upon. The impact upon organisations is multi-dimensional and profound, affecting both internal and external processes and structures in new and unexpected ways” (8).

Also, the appearance of DT has shaped a new world for entrepreneurs. Nambisan, Wright, and Feldman (2019) expressed that “the emergence of novel and powerful digital technologies, digital platforms and digital infrastructures has transformed innovation and entrepreneurship in significant ways. Beyond simply opening new opportunities for innovators and entrepreneurs, digital technologies have broader implications for value creation and value capture (9).

Another relevant element in DT is innovation and value creation. Galindo-Martín, Castaño-Martínez and Méndez-Picazo (2019) expressed that “the literature traditionally has focused its attention on the relationship between innovation and entrepreneurial activity. From this perspective, new innovations are accompanied by digital transformations that enhance value creation. However, it is also important to consider the effect of digital dividends on society overall as well as on entrepreneurship activity. Studies generally do not address this latter possibility" (10). They point out the importance of assessing DT's results in society much more than in companies or entrepreneurs. This point of view focuses in the fact that DT's effects in the community are also important.

In specific regions, DT has also produced a significant impact. Berger (2015), indicated that "the digital transformation of industry is creating tremendous opportunities for Europe – and confronting it with huge challenges. The possibilities opened up by connected, more efficient production and new business models are highly promising, yet the risks are equally dramatic. By 2025, Europe could see its manufacturing industry add gross value worth 1.25 trillion euros – or suffer the loss of 605 billion euros in foregone value added. The digital transformation of industry is also driving a radical structural transition in Europe's economies. New data, connectivity, automation and the digital customer interface are challenging existing value chains. Companies must take a long, hard look at their products and skill sets. And they have to improve their digital maturity if they are to recognize new opportunities, develop suitable offerings and get them to market quickly". (11).

As well, Berger also mentioned that DT has emerged as a "connector" between all components of economy. "We understand the digital transformation as the seamless, end-to-end connectivity of all areas of the economy, and as the way in which the various players adapt to the new conditions that prevail in the digital economy. Decisions made in connected systems affect data exchange and analytics, the calculation and assessment of options, the initiation of actions and their consequences" (11).

The mentioned argument from Berger has a close relation with supply chains. As soon as all economy's componentes get together or, at least, relates closer, all operational supply chains would also change. "Given seamless connectivity, disruptors can break value chains down into their smallest elements and then, thanks to low transaction costs, reassemble them. However, this atomization will also lower or even eliminate the barriers to market entry. In some cases, it will even do away with the need for lots of fixed assets to handle production and logistics. Industry leaders who master complex processes and have built up a substantial capital stock cannot be certain of retaining their advantage in this highly volatile environment. That, too, is a lesson quickly learned from the example of mobile communications. Similar developments are already becoming apparent in the retail sector" (11).

In other areas of economy, DT also has generated a deep mark. Belloch (2012), said that "the new digital technologies related with information and communications, in general terms, are the ones that are closed to three main factors: computer science, micro-electronics and communications. They are not only related with them, but they interact between each other in order to obtain new communication realities" (12).

Additionally, Tello Leal (2007) mentioned that “information and communications technologies is a concept that contemplates all technology, ways used to create, storage, exchange and process information in all its modalities, such as data, voice conversations, images fixed or in motion, multimedia presentations, etc. Particularly, these technolgies are closed related with computers, software and telecommunications devices” (13).

As seen so far, DT has a wide concept that impacts large areas of business. Its ramifications are very extended and reaches almost every human activities. In the mentioned articles, it is flawless that the digital transformation process is a notion with a wide variety of concepts. What is quietly clear is that is a migration within one point of origin to a final point of destination, in which the insertion of digital technologies plays a key role.

Digital Transformation and Data: crucial relationship

As mentioned before, DT generates disruptions and changes in a wide variety of activities. In companies, for example, as soon as managerial levels executes and conducts projects in which digital technologies are inserted, a clear result is expected: savings, Return over the Investment (ROI), better market position, new customers, better contract's conditions with providers, more customer-satisfaction, increase in sales and revenue, costs cuts, etc. The best way managers or supervisors can calculate or evaluate such expected results is through the use of data.

From my experience, the only way to monitor the evolution of an economic-social phenomenon such as DT, is through data, and that brings along an intensive research in time.
Gray and Rumpe (2017) expressed that "deconstructing the term from its two primary words, we identify two well-known concepts. "Transformation" describes a general process that starts with some initial situation that moves toward a changed, and supposedly better situation. Maybe that in this case the word transformation is not the best word choice because the underlying transformation may never meet a stable end, but rather undergo a continual set of evolutionary optimizations related to new forms of business, production, logistics, medicine or other changes within the targeted domain. "Digital" suggests that many changes in society, business and industry will be driven by information technologies that allow data to be processed in real-time and even used to intelligently derive information to finally provide stakeholders with improved knowledge about their processes and products" (14).
Such authors focused on the fact that data must be processed to generate knowledge about anything. Without data processing, there would not be new knowledge, new insights. Thus, the usage of data is crucial in order to see what is going on with DT's process within an organization.

In addition, the mentioned practice of data usage to monitor DT's process in organizations, has been widely used in business areas worldwide, regardless of company's size or mission. Schwertner (2015) indicated that "the volume of business data (terabytes and increasingly petabytes of information) suggests why managing and analysing it is a challenge" (15). Such large volumes of data demands a new skill in organization's workforce: data science.
Precisely, Gölzer and Fritzsche (2017) reaffirm the argument mentioned in the last parapraph: "With increasing importance of Big Data in the context of the digital transformation, the opposite will be the case: business structures will evolve based on the potential to develop value streams offered on the basis of new data processing solutions". (16). According with such authors, the importance of data in face of DT is crucial. They propose the circumstance that businesses evolve around data-processing-capacity. At this point, due to their research, a new interpretation comes up: commonly, some managers have thought that data changes as soon as organizations change; but now, Gölzer and Fritzsche propose that is the contrary…

organizations might evolve as soon as data-processing evolves too, because such discipline finds new ways to do things every day; it finds new paths, new markets and knocks down old paradigms.

The fact that manual tasks have switched to automated operations within the last years, has brought along the necessity of having a quantitative background to justify and evaluate such automation processes. For example, in the industrial market, this situation has generated a huge change in all sides. Rogers (2017), has explained that “one of the first steps for digital transformation in industrial plants and facilities is automating manual data-gathering processes, an activity often referred to as digitization” (17). Rogers added that data has been a crucial tool to monitor industrial performance in face of DT, especially when “maintaining the status quo is no longer acceptable in the process industries due to building pressure from a number of areas” (17).

Hence, data is at the core of digital transformation. Roedder, Dauer, Laubis, Karaenke and Weinhardt, (2016) reaffirmed this fact saying that “the digital transformation enables new business models and enhances business processes by utilizing available data for analytics, prediction, and decision support” (18).

Also, data is key to make good decisions in DT era. Newman (2018) said that “at the center of all of these technological trends and in the center of this list, falls the linchpin to so many of these trends and to digital transformation as a whole. Data is key to companies being able to make good decisions about products, services, employees, strategy and more. We won’t see a slowdown anytime soon. As recent data has shown we have created 90% of the world’s data in the past year, research is also showing that we are only using 1% of the data effectively”. (19).

Therefore, after this panoramic view, there is no doubt of how important data is for DT process analysis. In addition, data provides the supplies or consumable goods about how to evaluate such process in time. Hence, data science is the tool to process such data in order to generate value through the creation of new knowledge and insights.

CHAPTER 2:

DATA SCIENCE: ITS IMPORTANCE TO MANAGEMENT

Data Science: a key tool in management

Actually, Data Science is extremely important in management. Nowadays, when organizations and markets worldwide generate large amounts of data of any kind, this discipline has appeared as a crucial tool to process and analyze such data.

Kotu and Deshpande (2018) expressed that “we have run out of adjectives and superlatives to describe the growth trends of data. The technology revolution has brought about the need of process, store, analyze and comprehend large volumes of diverse data in meaningful ways. However, the value of the stored data is zero unless it is acted upon.”(20).

“Data Science is a collection of techniques used to extract value from data. It has become an essential tool for any organization that collects, stores, and processes data as part of its operations. Data Science techniques rely on finding useful patterns, connections and relationship within data. Data Science is also commonly referred to as knowledge discovery, machine learning, predictive analytics and data mining” (20).

Thus, “Data Science stars with data, which can range from a simple array of a few numeric observations to a complex matrix of millions of observations with thousand of variables. Data Science utilizes certain specialized computational methods in order to discover meaningful and useful structures within a dataset” (20).

Also, Data Science uses techniques such as statistics, visualizations, data preparation and data mining to process all kinds of raw data, in order to produce final products that can be sent to managerial levels to be used in making business decisions as accurate as possible.

In terms of management, data science is absolutely crucial. Everyday, managers worldwide face the challenge to increase their organization’s stock value in front of shareholders. By the end of the day, that is the final mission of CEO’s and CFO’s: increase the value of stocks. Obviously, to increase such value, companies must strengthen its competitive position in market. To improve such position, they must compete within a fierce market full of good-skilled competitors for a limited quantity of opportunities and customers. The way they obtain more customers, they would increase its sales and revenues and, consequently, the stock’s value would also increase.
Historically, companies have used an almost infinite variety of strategies to compete in market in order not only to survive, but to succeed and, if its possible, dominate. A lot of marketing, financial, investment and management plans have been executed to obtain such purpose. But recently, within recent years, a new tool has appeared in stage with a “lead actor role”: Data Science.

But, why Data Science? Organizations ingest and produce tons of data everyday. Some of them do not even visualize what kind and how much data they manage. In these cases, data can take place of sales, banking transactions, supplies purchases, market researches, advertising issues, social media posts, digital dialogues with customers, sales devolutions, etc. How to retrieve all that variety of data and transform it into a meaningful-consolidated reports with useful insights for managers? The answer is pretty simple: using Data Science techniques.

McAfee, Brynjolfsson, Davenport, Patil, and Barton, (2012), mentioned that "data-driven decisions are better decisions—it's as simple as that. Using big data enables managers to decide on the basis of evidence rather than intuition. For that reason it has the potential to revolutionize management. The managerial challenges, however, are very real. Senior decision makers have to embrace evidence-based decision making. Their companies need to hire scientists who can find patterns in data and translate them into useful business information. And whole organizations need to redefine their understanding of "judgment." (21).

Thus, within the last years, companies and managers are facing a huge challenge: how to manage such large amounts of data. Callahan, Freire, Santos, Scheidegger, Silva and Vo (2006) mentioned that "scientists are now faced with an incredible volume of data to analyze. To successfully analyze and validate various hypothesis, it is necessary to pose several queries, correlate disparate data, and create insightful visualizations of both the simulated processes and observed phenomena. Often, insight comes from comparing the results of multiple visualizations". (22).

Therefore, the usage of Data Science techniques are crucial in management, in order to monitor the market: customers, competitors, providers and environmental participants such as government's policies. Additionally, it is absolutely relevant to evaluate organization's own performance in face of challenges, corporate objectives and the pursue of getting a better-competitive market position.

Data Science: a new tool for market research

According to Provost and Fawcett (2013), “one of the most critical aspects of data science is the support of data-analytic thinking. Skill at thinking data-analytically is important not just for the data scientist but throughout the organization” (23).

In addition, Qadadeh and Abdallah (2018), mentioned that “companies nowadays are continuously working to increase their competitiveness. The availability of big data for Customer Relationship Management (CRM) and data warehouses, with high dimensions, the need to use data mining advanced technologies has been increasing significantly. The usage of data mining algorithms might help businesses to find interesting knowledge in its customer’s data both demographic and behavioral, then it is the marketing experts’ responsibility to use these insights in designing the company marketing campaigns to fulfill customer’s interests” (24).

Related with the mentioned arguments so far, the task of collecting, processing and analyzing data from the environment is called market research. The most organizations execute accurate market reseach -specially from customers-, the better competitive advantage they would obtain.

Now, market researches can be developed to collect data from outside the organization (customers, competitors, providers, etc). On the contrary, it can also be applied to obtain crucial information within internal areas of the organization (operational and administrative processes). In face of customers, for example, one of the most important objectives of executing these kind of researches is mapping their consuming behavior, in order to estimate and anticipate their needs. In face of internal issues, one good example might be the fact of monitoring product-processing times in case of manufacturing companies, in order to increase efficiency.

As I have mentioned previously, DT is capable to change operational processes, either external or internal issues of companies, due to the insertion of digital technologies. The variations in processes, either quantitative or qualitative, should be calculated though the execution of market researches (data collection). Consequently, such data collection should be developed by Data Science techniques. Precisely, this is the link that unifies both concepts: Data Sciencie and Market Research.

McQuarrie (2015) points a very interesting argument: “You should consider doing market research whenever you feel unable to decide because you lack information from or about customers" (25). Also, he focuses on the fact that market research is justified only if managers face a decision: "If you are not faced with a decision, you can't really justify doing market research" (25). Last statement was clear: market research supports decisions; such decisions must be accurate for the good of organizations. Another extra annotation: doing market research just for fun or just to execute it without any specific purpose or decision, does not make sense and would be a total waste of money and time.

Therefore, as soon as Data Science techniques help collecting data from a wide variety of sources, it is a fantastic instrument to support market research efforts in organizations. Logically, a decision-necessity must be involved in the middle to justify such efforts.

In cases in which DT has generated disruptions regardless of their nature, market research efforts must be involved, in order to calculate such variations. In these situations, Data Science techniques should provide market research´s efforts a real possibility to collect, process and generate accurate results for managerial levels.

CHAPTER 3:

TYPES OF DATA

Types of data

As mentioned before, there are tons of data in market from a wide variety of sources. Sometimes is easy to find and consolidate data, but sometimes is very difficult to access and manage databases because, in the majority of cases, such information is incomplete, inaccurate and disorganized, and, in some cases as well, data does not exists at all and, consequently, huge gaps appears in data-collection's necessities. The way an organization manages its own data, would define the manner it takes good or bad decisions, accurate or innacurate managerial actions.

There are three types of data:

1. **Structured data.** It is data that has been stablished in a fixed format.

2. **Unstructured data.** It is data that does not have any specific format.

3. **Semi-structured data.** It is data that contains both types of data: structured and unstructured.

Structured data

An important quantity of organizations in market manages structured data because they do not have, usually, standardized procedures to work with data, and this issue relates to the fact of defining strict measures at the moment of creating, adjusting, analyzing, reporting and storaging datasets.

Therefore, if a company or organization manages structured data, is a clear reflect of a consolidated-high standard of operational and managerial maturity, closely related with a solid data-management operational structure.
Examples of structured data could be payroll, customers, providers and distributors databases, in which companies consolidate crucial information about them: salaries, points of contact, addresses, volume of traded goods, financial resources spent, delivery times, specific statistics, etc.

Unstructured data

In contrast to Structured Data, another relevant quantity of organizations in market manages Unstructured Data because they do not have standardized procedures to work with data, and this issue relates to the fact of defining strict measures at the moment of creating, adjusting, analyzing, reporting and storaging datasets.

Usually, unstructured data consists of all internal information generated within an organization, because it has been created without following an specific path of defined structure. In the majority of cases, unstructured data is made of large amounts of information that, generally, is disorganized.

Semi-Structured data

This kind of data is a combination between the structured and the unstructured types. The line between them is not clearly defined.

CHAPTER 4:

QUANTITATIVE DATA

Quantitative Data

Quantitative Data is data that can be measured and expressed numerically. Thus, every type of data that can be expressed in numbers, can be determined as quantitative. For instance, the height of a person, a salary, the population of a city, the weight of a box, a test score, the quantity of tasks of an operational process and the price of a house, could be some examples of Quantitative Data.
There are some characteristics of Quantitative Data:

1. Is considered as Structured Data.

2. It answeres the question of *how much or how many.*

3. Due to the fact that it involves numbers, statistics play a key role.

4. At the end of an analysis, it recommends an specific course of action.

Additionally, Quantitative Data has two subgroups:

1. Discrete Data. It can take only certain values. For instance, the number of citizens of a country.

2. Continous Data. It can take any value within a specified range. For example, the price of a stock.

CHAPTER 5:

TIME SERIES DATA

Time-Series data: general ideas

Esling and Agon (2012) indicated that "in almost every scientific field, measurements are performed over time. These observations lead to a collection of organized data called *Time Series*. The purpose of time-series data mining is to try to extract all meaningful knowledge from the shape of data" (26).

Moreover, Fu (2011) expressed that "a time series is a collection of observations made chronologically. The nature of time series data includes: large in data size, high dimensionality and necessary to update continuously. Moreover time series data, which is characterized by its numerical and continuous nature, is always considered as a whole instead of individual numerical field. The increasing use of time series data has initiated a great deal of research and development attempts in the field of data mining" (27).

The task of collecting data in time requires patience and perseverance of the researcher, even in environments in which such collection seems to be easy. Also, researchers must learn how to get over some threats that attempt to stop the work. In the majority of cases, there are no "sensors" collecting data automatically; researchers must execute a wide variety of strategies to collect them manually and to keep such task in track. An important issue at this point is that, in general terms and in almost all data-collecting tasks, there should not be interruptions in such series, or what I call "blank spaces" in data series. A high-quality data-series (dataset) of any variable is the one that has no "blank spaces" in time.

Indeed, Guralnik and Srivastava (1999) expressed that "sensor-based monitoring of any phenomenon creates time series data. The spacing between successive readings may be constant or varying, depending on wether the sampling is fixed or adaptive. The overall goal is to obtain an accurate picture of the phenomenon with minimum sampling efforts" (28).
The mentioned authors wrote about a crucial element: sampling. Samples are statistical elements to work with a smaller quantity of objects (observations) from a whole and bigger population. In some cases, it is absolutely impossible to collect data from a whole population, and that is why researchers decide to proceed with statistical techniques to define a smaller sample that represents the whole group. However, at the time of time-series data collection, sampling is not always an accurate strategy, especially by the fact that such series must reflect the highest possible statistical-confidence level.

Another crucial annotation made by Guralnik and Srivastava (1999) is the existance of "events" in temporal sequences. They mentioned that "an issue that has received scant attention is of deriving an event sequence from raw sensor data" (28). They stated that, depending on the variable, sometimes is relatively easy to collect data, but there are cases in which such collection is very difficult.

"Consider a dynamic phenomenon whose behavior changes enough over time so as to be considered a qualitatively significant change. Each change is an event. An example is the change of highway traffic from light to heavy to congested. Another example is the change of a boiler from normal to super-heated. The specific problem we address is of applying data mining techniques to identify the time points at which the changes-events occur" (28).
My experience in Data Science and in metric-construction tasks, has surrounded, indeed, around time series data and, more specifically, the identification and the calculation of the mentioned "events". I have defined such events as "points of disruption".
What I particularly love of time series data analysis is the possibility to construct visualizations to look at the whole evolution of a certain variable, from its point of origin until its destination. The fact of looking its total route gives me the chance, precisely, to identify disruptions, or as Guralnik and Srivastava appointed, events. For me, that has been the core of my recent work.

In addition, Ralanamahatana, Lin, Gunopulos, Keogh, Vlachos, and Das (2005), has appointed that "much of the world's supply of data is in the form of time series. In the last decade, there has been an explosion of interest in mining time series data. A number of new algorithms have been introduced to classify, cluster, segment, index, discover rules, and detect anomalies/novelties in time series. While these many different techniques used to solve these problems use a multitude of different techniques, they all have one common factor; they require some high level representation of the data, rather than the original raw data. These high level representation are necessary as a feature extraction step, or simply to make the storage, transmission, and computation of massive dataset feasible" (29).

Another definition of Time Series is the one developed by Zhao, Lu, Chen, Liu and Wu (2017), that stated that "time series is an important class of temporal data objects, and can be easily obtained by recording a series of observations chronologically, e.g. price of stocks, electrocardiogram (ECG) and brightness of a star. Recently, time series data mining has attracted great interests and initiated various researches" (30).

In the mentioned definitions, such authors talked about "objects" of a time series, which constitutes a key element in a group of observations within a certain period of time. The summatory of objects of a time series are the elements researchers must take into consideration to develop the whole analysis of its evolution in time.

At the same reasoning, time series data could constitute a vector, which is a very common concept used in Data Science and technology. In Computer Science, a vector is a group of elements or objects that have common characteristics between each other (same type) and they are usually ordered following a determine pattern. Through a vector or a group of vectors, data could be accesed, analyzed, classified and correlated in an easier way.

Now, located very close to Time Series Data we find the correspondent analysis, in order to construct a discipline that is called Time Series Analysis. Time Serie Data itself does not say anything; it needs an analysis component in order to come up with meaningful results.

Nielsen (2019) defined Time Series Analysis as “the endeavour of extracting meaningful summary and statistical information from points arranged in chronologial order. It is done to diagnose past behavior as well as to predict future behavior” (31). In addition, Nielsen has mentioned that Time Series Analysis has been used widely in a diverse quantity of fields, such as medicine, weather, statistics, economics and astronomy.

One crucial aspect of Time Series Analysis, according to Nielsen, is the availability of data. “Progress in statistics, data analysis and time series has always depended on when, where and how data was available and in what quantity. The emergence of time series analysis as a discipline is linked not only to developments in probability theory, but equally to the development of stable nation states, where recordkeeping first became a realizable and interesting goal” (31).

As mentioned, as much data available, the more accurate would be the Time Series modeling, and the more complete would be its correspondent analysis. This issue is closely related with the fact that besides the existance of a strong mathematical model of Time Series Analysis, data availability is absolutely crucial. Without data, in spite of a strong model of algorithms, there would not be a high-quality-analysis.

Time-Series data: where to find data

Now that general ideas and concepts of Time Series Data have been covered so far, it's important to realize where to find data.

The most common sources of data are the ones that have been stored in specific repositories; could be physical servers or local disks, or virtual environments such as the Cloud or virtualized servers. These data could be internal or external an organization.

According to my experience, the best source of data to come up with a high qualtity Time Series Analysis, is the one that could be collected live through time. As mentioned before, the task of collecting data in time requires patience and perseverance of the researcher, even in environments in which such collection seems to be easy. Also, researchers must learn how to get over some threats that attempt to stop the work. In the majority of cases, there are no "sensors" collecting data automatically; researchers must execute a wide variety of strategies to collect it manually and to keep such task in track.

Indeed, according with Guralnik and Srivastava (1999) "sensor-based monitoring of any phenomenon creates time series data" (28). This argument implies the usage of automatic processes to collect data, which is a common strategy when researchers work with Big Data from a wide amount of sources. In cases in which researchers need to collect smaller quantity of data, a manual-collecting task would be recommended, as long as the work does not stop in time.

The peak of internet actually has brought a new era in data collection, especially, for the possibility to access to large amounts of data in an automatic way.

Namey, Guest, O'Regan, Godwin, Taylor and Martinez (2020) mentioned that "internet-based platforms are increasingly used to collect qualitative data. Qualitative data collection is no longer synonymous with face-to-face research, as researchers now use a variety of online platforms to conduct focus groups (FGs) and individual interviews (IDIs)." (32).

In addition to the peak of internet, not less relevant is the peak of smartphones, in an age in which, in one way, all kinds of data can be accessed using our fingertips and, in the other way, all kinds of data can be collected from such devices. One example of this phenomenon is the research conducted by Onnela (2021) related with cognitive phenotypes data-collection, in which she established that "the broad adoption and use of smartphones has led to fundamentally new opportunities for capturing social, behavioral, and cognitive phenotypes in free-living settings, outside of research laboratories and clinics. Predicated on the use of existing personal devices rather than the introduction of additional instrumentation, smartphone-based digital phenotyping presents us with several opportunities and challenges in data collection and data analysis. These two aspects are strongly coupled, because decisions about what data to collect and how to collect it constrain what statistical analyses can be carried out, now and years later, and therefore ultimately determine what scientific, clinical, and public health questions may be asked and answered" (33).

Another field that requires new data-collection skills is the audit field. As soon as organization's operations have become more and more complex, and as soon as the data-ingest has become more and more intense, control and audit tasks have to be relaunched in order to be leveled with such growth of data-usage.

Appelbaum, Kogan and Vasarhelyi (2017) have expressed that "modern audit engagements often involve examination of clients that are using Big Data and analytics to remain competitive and relevant in today's business environment. Client systems now are integrated with the Cloud, the Internet of Things, and external data sources such as social media. Furthermore, many engagement clients are now integrating this Big Data with new and complex business analytical approaches to generate intelligence for decision making. This scenario provides almost limitless opportunities and the urgency for the external auditor to utilize advanced analytics" (34). Thus, audit field must move toward to Big Data and digitalization in order to work as fast as the growth's speed of their clients in terms of data-ingest and data-usage.

The mentioned examples are just a few cases in which the era of "data explosion" and it's correspondent peak of data-collection has shown its power. As such cases have shown, data is everywhere and it is part of every single human activity. Where to find in order to collect it? Depends on the nature of it's origin and in the level of knowledge of the data-generator. How to collect it? Depends in the related amount. The "golden rule" here consists in keeping the track in the collection-task in order to avoid the previously mentioned "blank spaces".

One crucial element at this point is the nature and characteristics of what I call the "data-generator". It could be a company, a person, a machine, a server, an operational process, an administrative procedure or even a sensor. The better researchers can dig deeply on its nature, the most they can develop an accurate strategy to collect data from them. It turns out to be illogical the fact of collecting data from a "generator" which researchers do not know deeply; they would not be able to analyze accurately the data loaded. By that, the research's final product or expected results would not be considered as a reliable one.

However, knowing deeply a “data-generator” takes time. Knowing the “whole picture” can not be built in one day; researchers must develop strategies to dig in all it’s details through a patient manner. For example, talking to employees, customers, providers, experts, studying bibliography, reading contracts and related legal documentation, analyzing it’s history and background and studying all proceses one by one, could be some recommended plans to know better a company from whose data would be collected for research purposes.

Time-Series data: looking for history

One of the most relevant purposes that explains why researchers try to collect time-series data is the necessity to build history, records or precedents of a certain variable in time.

Such task is crucial not only to construct the evolution in time of a determined variable, but to set up an accurate model for predictions and estimations. This topic of building estimations analysis and algorithms is an universe itself.

Focusing in the past, taking a look back in time series data is important because there is a possibility to visualize the evolution of a variable from its origin to present. Taking in hand the premise that establishes that what we have now in present is the result of what happened before, creates the necessity to know as much as possible from what ocurred during the past.

Hence, everytime researchers try to collect historic data from a certain variable, they are looking for its evolution within the past to try to explain a determined present situation. From a specific dataset, they build special visualization plots and summarised data-frames to understand better its journey from its origin to present. With such data collected, they would be able to construct a “landscape” as accurate as possible about it, and try to understand its actual situation.

The identification of patterns and potential anomalies in historic datasets is also a key task in this topic. Johannesmeyer, Singhal and Seborg (2002) expressed that “for many engineering and business problems, it would be very useful to have a general strategy for pattern matching in large databases. For example, the analysis of an abnormal plant condition would benefit if previous occurrences of the abnormal condition could be located in the historical data” (35). Looking for specific patterns in historic data could be absolutely clue to justify a determined present behavior of a variable. Also, such analysis is very important to detect anomalies in data, in order to explain possible deviations from common-known standards.

Blossfeld, Hamerle and Mayer (2014), executed a fantastic research regarding historic data analysis. They developed a new method related with such task, and named it as “Event History Analysis”. “By Event History Analysis we mean statistical methods used to analyze time intervals between successive state transitions or events”. A wide range of statistical tools are available today to analyze event history data as exemplified in a variety of models, approaches and methods” (36). They made some important annotations: 1. Event history analysis applies stochastic models that are not often found in normal applications. 2. Incomplete or censored data frequently occur only in very specific research designs. 3. Due to the development application of this methods in various disciplines such as medicine, demography, technology, economics and the social sciences, the terminology is not uniform and thus the methods are not easily accesible to the user” (36).

Addtionally, one of the most remarkable insight of their research, is the principal advantage of performing the mentioned method, “ The major advantage of an event oriented observation plan that concurs with the growing interest in the analysis of change is the fact that it permits an adequate representation of changes in qualitative variables which may occur at any point in time” (36).

They mentioned a key element during their research: capacity to identify changes at any time. From this insight, a pretty important factor must be pointed: the task of colleting historic data of any variable must conduct to a change, variation or a disruptions identification.
Another crucial element that can be extracted from their work, is the fact that, as I mentioned before, this work demands a huge effort from researchers. They indicated that “regardless which of the described procedures to record event history data is selected, it is always an extensive and costly exercise” (36).

Thus, examining data from past periods of a certain variable is a hard process for researchers, but absolutely worthly. The benefits of performing such task bases itself in the fact that is trully relevant to build tendencies and patterns to explain situations in present. Additionally, these kind of exercises give the chance to identify changes, variations or disruptions in tendencies.

CHAPTER 6:

DATA DISRUPTIONS

Data Disruptions

Within the last sections, I have covered the essential elements of time-series data and how important is such collection of information to construct evolutions, patterns and tendencies in datasets.

In my experience, one of the most attractive and interesting issues of collecting historic data of any variable and building time-series excercises, is the possibility of analyzing disruptions. What is a disruption? Merriam-Webster online dictionary defines such concept as “the act or process of disrupting something: a break or interruption in the normal course or continuation of some activity, process, etc” (37). Hence, such dictionary mentioned some crucial secondary definitions: “to cause upheaval in an industry, market, etc. To successfully challenge (established businesses, products, or services) by using an innovation (such as a new technology or business model) to gain a foothold in a marginal or new segment of the market and then fundamentally changing the nature of the market” (37).

Let’s analyze a little deeper such secondary ideas developed by Merriam-Webster. First, they cited the word “Upheaval”, which is a concept related with turbulence, shaking and mixing. Evidently, there must be a force to generate a turbulence, a shake; if everything remains calm without any change, there would not be a turbulence behind. Second, they mentioned the word “Foothold”, which is an idea related with finding a support point when a person is climbing a mountain. This metaphor can be applied to management: organizations must find footholds everytime they develop an innovative project.

At this point, why is relevant the usage and analysis of those two words? Because the definition itself of the word Disruption does not come alone; it brings along secondary and crucial elements: it generates an upheaval and could be considered as a foothold. My personal intepretation of the analysis performed by Merriam-Webster, is that the appearance of a disruption, automatically, generates a turbulence, a change. Thus, as soon as organizations insert an innovative element into a process, a challenge is produced; such disruption generated could be utilized as a foothold to justify an eventual change in market.
As a complementary argument so far, Merriam-Webster displayed some synonyms of the word Disruption. They mentioned the words “break, break up, bust, disintegrate, dismember, fracture, fragment and rive” (37). Those other secondary words enriche the analysis of the scope of the studied concept of Disruption. Therefore, is clear that a disruption is related with a significant change, and a break in a tendency.

Hence, taking into consideration that disruptions could be considered as “breakup-points”, it is extremely important it’s study and analysis in time-series data. Precisely, this has been the core of my recent work.

Ramezani and Camarinha-Matos (2019) indicated that “today’s business world is continuously challenged by unexpected disruptive events, which are increasing in their frequency and effects. As a consequence, it is plausible to foresee future scenarios in which turbulence and instability are no longer considered as episodic crises, but rather somewhat the “norm” or the default status. This trend naturally raises the question of how organizations can strive and even gain in such disruptive environments, and which characteristics are required for combating disruptions. Resilience and antifragility are two emerging approaches to handle disruptions” (38).

From that point on, the mentioned authors consider that “unexpected disruptive events” are common in market and organizations must adapt to them and, much more beyond, must assess them. Therefore, according to their analysis, they must not be considered anymore as “crisis” but as “norm” (38)… something usual. Hence, from that point of view, my personal contribution on this might be that is absolutely critical for organizations being not only familiarized with them, but capable to make an additional effort in order to develop quantitative analysis to identify, calculate and evaluate such disruptions.

Therefore, according to the arguments mentioned so far, a disruption is much more than a quantitative variation. A disruption brings along a change in some crucial elements of organizations: insertion of digital technologies, new ways to do things for workforce, innovative operational processes and a new culture at all. The same reasoning can be applied to the Digital Transformation process. It is much more than a new technological disruptive event. It is a change of culture, a total-mindset change within the whole organization.

In spite of the stated fact detailed in the last paragraph, I will focus in quantitative variations as a new approach- methodology to calculate and evaluate DT process. Such variations would be the change in quantity of manual tasks in operational processes due to the insertion of digital technologies during a specific moment in time. The variations of every single operational process will be consolidated, in order to develop weighted coefficients (such methodology will be detailed in following sections of this book). At his point, data disruptions constitutes the core of DT Quantum Model, because it takes into consideration changes in historic data tendencies due to disruptive events such as the insertion of digital technologies into determined operational processes.

Therefore, the DT Quantum Model adapts “data disruption” concept as an specific moment in a time-series-data (dataset) in which its tendency (manual tasks) suffers a clear change (rise or fall); the correspondent curve suffers a variation on its slope and it shows a descent or ascent on its tendency.

CHAPTER 7:

INTERRUPTED TIME SERIES ANALYSIS

Interrupted Time Series Analysis

McDowall, McCleary and Bartos (2019), mentioned that " Interrupted Time Series Analysis (ITSA) is a toolbox for researchers whose data consists of a long sequence of observations, say N>= 15 observations, measured before and after a treatment or intervention. Sometimes the treatment or intervention is implemented by the researcher, and other times it occur naturally or by accident" (39).

In addition, Linden (2015) expressed that "in an interrupted time-series analysis, an outcome variable is observed over multiple, equally spaced time periods before and after the introduction of an intervention that is expected to interrupt its level or trend" (40).
Also, Ferron and Rendina-Gobioff (2005) indicated that "interrupted time-series designs allow researchers to examine the effect of an intervention. Multiple observations are obtained prior to the intervention to establish a baseline. Multiple observations are also obtained after the intervention. Effects are demonstrated when the observations after the intervention deviate from expectations derived from baseline projections" (41).

Another argument cited at this point is the one expressed by Penfold and Zhang (2013), in which they stated that "interrupted time series (ITS) analysis is arguably the strongest quasi-experimental research design (42).

Linden and Yarnold (2016) also performed a research in which they indicated that "single-group interrupted time series analysis (ITSA) is a popular evaluation methodology in which a single unit of observation is being studied, the outcome variable is serially ordered as a time series and the intervention is expected to 'interrupt' the level and/or trend of the time series, subsequent to its introduction. Given that the internal validity of the design rests on the premise that the interruption in the time series is associated with the introduction of the treatment, treatment effects may seem less plausible if a parallel trend already exists in the time series prior to the actual intervention. Thus, sensitivity analyses should focus on detecting structural breaks in the time series before the intervention" (43).

So far in this section, I have added five different definitions and points of view of the general concept of Interrupted Time Series Analysis. Although its concept and application in research is much more technically-complicated, it is a research design in which the analysis of an "intervention" over a historic-dataset is performed in order to visualize changes in tendencies.

The analysis performed to construct the *DT Quantum Model*, is based in a methodology in which a study of a historic-dataset related with the quantity of manual tasks of determined operational processes is executed. Due to the insertion of digital technologies in specific moments in time (intervention) an effect is expected in each of them: an “interruption” of such historic trend as a result of the automation of the related manual tasks. A variation is calculated for each operational process in which the digital technology had been inserted (before and after the introduction of an intervention). Then, all variations of all processes are consolidated and a weighted coefficient is calculated.

CHAPTER 8:

DT QUANTUM MODEL

Assumptions

DT Quantum Model is based in the following assumptions:

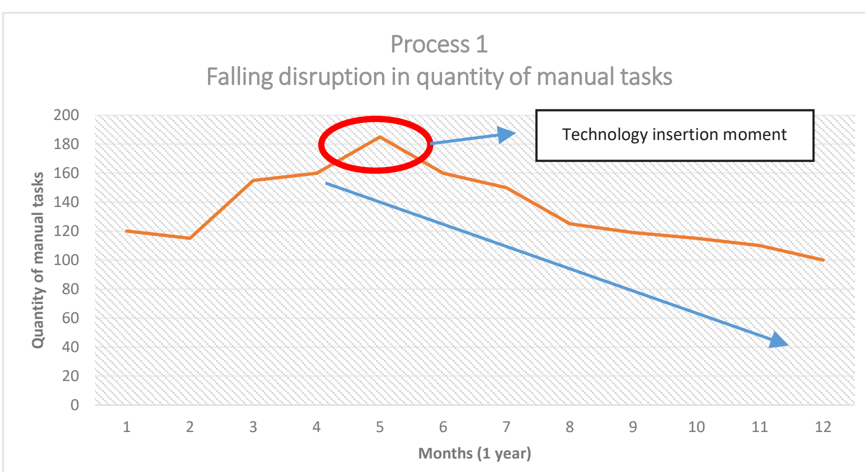
1. The Digital Transformation happens if, due to the insertion of digital technologies in an operational process, the quantity of manual tasks decreases.

2. It takes into consideration the quantity of manual tasks of one or more operational processes of an organization, during a determined period of time. The frequency of data collection of such quantity of transactions per process could be daily, weekly, monthly, annually, etc.

3. It takes into consideration the exact moment in time in which a digital technology was inserted to automatize or improve one or more of those operational processes; this event generates a disruption in the data range of the quantity of manual tasks of each operational process. This disruption could be of three types:

   a. Falling disruption: occurs when there is a falling difference (decrease) in the quantity of manual transactions of a certain process; in this case, means that the insertion of digital technologies generated a decrease in the quantity of manual transactions and, consequently, a positive digital transformation. The following image shows an example of this type of disruption:

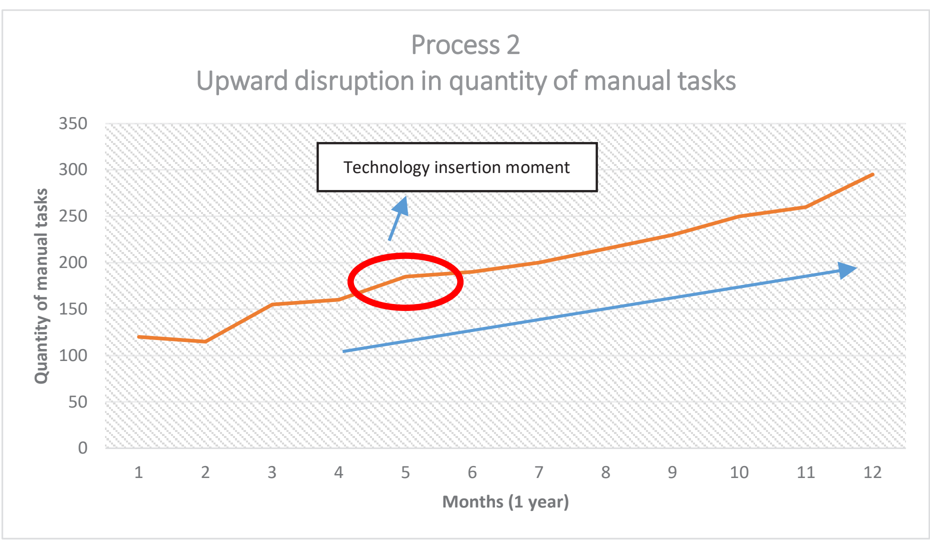
Image 8.1
DT Quantum Model. Example of a falling disruption



In this kind of disruption, due to the example shown (Image 8.1), the insertion of digital technologies produced less manual work for employees since the fifth month (exact moment of the insertion), and the tendency of manual tasks experimented a sustained decrease until the final month. In this case, the variation is immediate due to the insertion of technology.

b. Upward disruption: occurs when there is an upward difference (increase) in the quantity of manual tasks of a certain process; in this case, means that the insertion of digital technologies generated an increase in the quantity of manual transactions and, consequently, a negative digital transformation. The following image shows an example of this type of disruption:

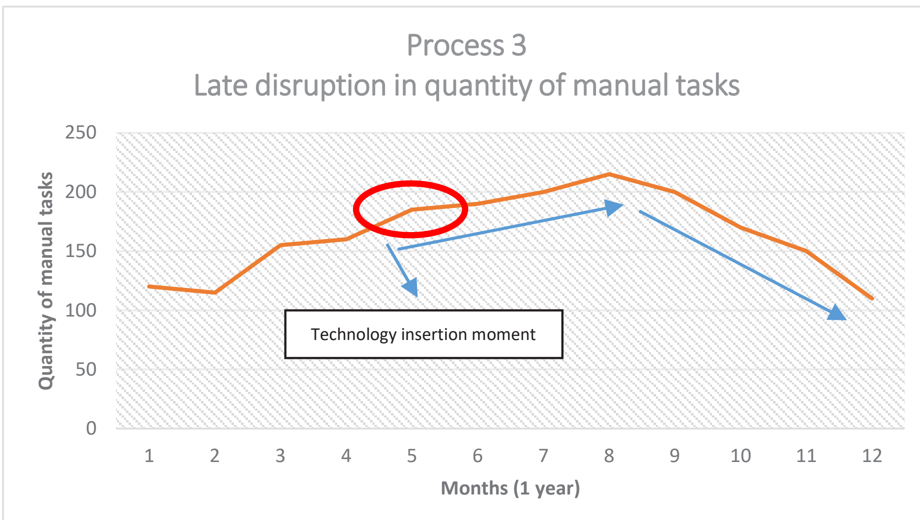
Image 8.2
DT Quantum Model. Example of an upward disruption



In this kind of disruption, due to the example shown (Image 8.2), the insertion of digital technologies produced more manual work for employees since the fifth month (exact moment of the insertion), and the tendency of manual tasks experimented a sustained increase until the final month. Sometimes, for some reasons, the insertion of digital technologies generates the contrary expected effect in the quantity of manual tasks.

c. Late disruption: occurs when the expected decrease in manual work due to the insertion of digital technologies in a certain process, happens late since the exact moment of such insertion. The following image shows an example of this type of disruption:

Image 8.3
DT Quantum Model. Example of a late disruption

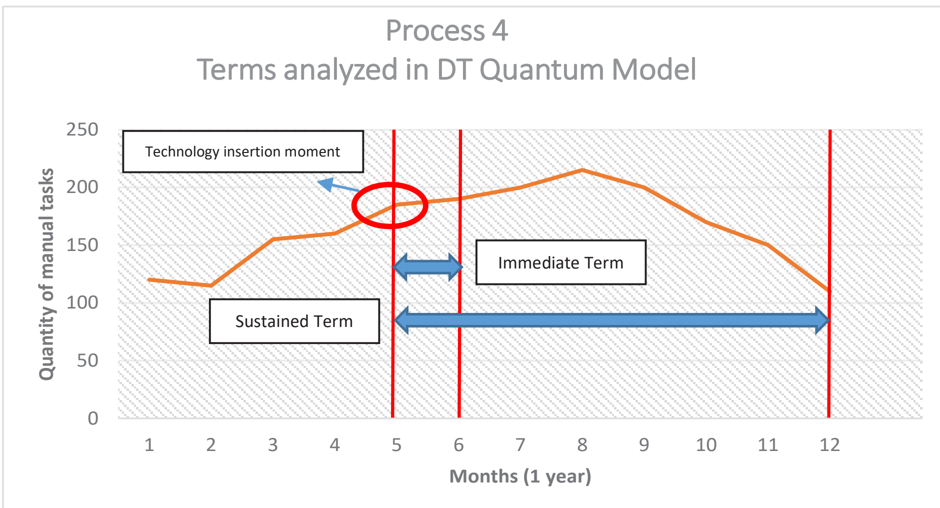


In this kind of disruption, due to the example shown (Image 8.3), the insertion of digital technologies produced less manual work for employees since the eighth month (not the exact moment of the insertion), and the tendency of manual tasks experimented a sustained decrease until the final month since then. Sometimes, for some reasons, the insertion of digital technologies generates a late effect in quantity of manual tasks. Such variations happen some time after the insertion of technology.

4. In the majority of cases, the highest values in time-series datasets of the quantity of manual tasks in operational processess, matches with the moment in which digital technologies were inserted.

5. Term analyzed: This research takes into consideration two types of terms since the exact moment of the insertion of digital technologies into an operational process. First, the **immediate term**: is the immediate moment after the insertion of technology (it referes if the variarion occurs the immediate following period: day, month, year). Second: the **sustained term**: is the effect generated by technology but some time after its insertion; it's effect is not immediate. The following image shows the difference between each type of term:

Image 8.4
DT Quantum Model. Example of immediate and sustained terms analyzed



The two different terms analyzed in *DT Quantum Model* are shown in Image 8.4. The immediate term takes into consideration the effect from the moment in which digital technologies were inserted and the month/week/year immediate after. The sustained term takes in consideration the variation from the moment in which technology was inserted and the month/week/year in which the whole analysis ends.

The objective of performing an analysis of both terms consists in determining the immediate effects of DT process, and also defining if the related organization is capable to sustain its effects in time.

First approach: DT Quantum Model Coefficients

Immediate Digital Transformation Coefficient (IDTC)

This coefficient measures the variation (percent) of the highest value (HV) of each historic dataset of quantity of manual tasks for each operational process, in relation to the immediate value (IV) experimented after the insertion of digital technologies. It measures the immediate disruption and how intense (or negative) has been the digital transformation process in the immediate moment due to the insertion of digital technologies. At the end, an average of every single coefficient of each operational process is calculated, in order to estimate a single weighted immediate coefficient. The formula, for each operational process, is as follows:

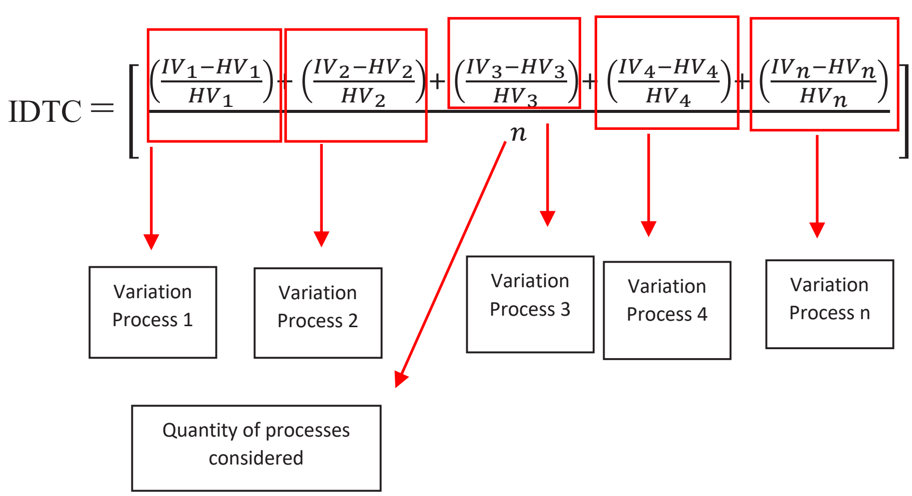
$$\mathrm{IDTC} = \left[\frac{\left(\frac{IV_1 - HV_1}{HV_1}\right) + \left(\frac{IV_2 - HV}{HV_2}\right) + \left(\frac{IV_3 - HV_3}{HV_3}\right) + \left(\frac{IV_4 - HV_4}{HV_4}\right) + \left(\frac{IV_n - HV_n}{HV_n}\right)}{n} \right]$$

Where:

IDTC = Immediate Digital Transformation Coefficient.
HV: Highest value of historic dataset of quantity of tasks for each operational process.
IV: Immediate value after the highest value in the dataset of quantity of manual tasks of each operational process.
n = the quantity of operational processes taken in consideration for the calculations.

The result of the formula will be a weighted coefficient, expressed in percentage.

Also:



Sustained Digital Transformation Coefficient (STCS)

This coefficient measures the variation (percent) of the highest value (HV) of each historic dataset of quantity of manual tasks for each operational process, in relation to the final value (FV) of the time range analyzed. It measures the disruption in time and how intense (or negative) has been the digital transformation process in a longer period of time due to the insertion of digital technologies. At the end, an average of every single coefficient of each operational process is calculated, in order to estimate a single weighted sustained coefficient. The formula is as follows:

$$\mathrm{SDTC} = \left[\frac{\left(\frac{FV_1-HV_1}{HV_1}\right)+\left(\frac{FV_2-HV_2}{HV_2}\right)+\left(\frac{FV_3-HV_3}{HV_3}\right)+\left(\frac{FV_4-HV_4}{HV_4}\right)+\left(\frac{FV_n-HV_n}{HV_n}\right)}{n}\right]$$

Where:

SDTC = Sustained Digital Transformation Coefficient.
HV: Highest value of historic dataset of quantity of manual tasks for each operational process.
FV: Final value of the dataset of quantity of manual tasks for each operational process.
n = the quantity of operational processes taken in consideration for the calculations.

The result of the formula will be a weighted coefficient, expressed in percentage.

Also:

$$\mathrm{SDTC} = \left[\frac{\underbrace{\boxed{\left(\frac{FV_1-HV_1}{HV_1}\right)}}_{\text{Variation Process 1}}+\underbrace{\boxed{\left(\frac{FV_2-HV_2}{HV_2}\right)}}_{\text{Variation Process 2}}+\underbrace{\boxed{\left(\frac{FV_3-HV_3}{HV_3}\right)}}_{\text{Variation Process 3}}+\underbrace{\boxed{\left(\frac{FV_4-HV_4}{HV_4}\right)}}_{\text{Variation Process 4}}+\underbrace{\boxed{\left(\frac{FV_n-HV_n}{HV_n}\right)}}_{\text{Variation Process n}}}{\underbrace{n}_{\text{Quantity of processes considered}}}\right]$$

At the end of the calculations, a summary table (Table 8.1) could be shown with the objective of ordering the final data:

Table 8.1
DT Quantum Model. Summary of results of IDTC and SDTC for each operational process

Process	Insertion of digital technologies	Immediate Digital Transformation Coefficient	Sustained Digital Transformation Coefficient
1	Yes	%	%
2	Yes	%	%
3	Yes	%	%
4	Yes	%	%
5	Yes	%	%
6	Yes	%	%
7	Yes	%	%
8	Yes	%	%
9	Yes	%	%
10	Yes	%	%
	Weighted coefficients	**IDTC%** Immediate Digital Transformation Coefficient (Weighted)	**SDTC%** Sustained Digital Transformation Coefficient (Weighted)

Second Approach: Calculate intensity of DT

The results of both coefficients (IDTC and SDTC) are in percentages, and the results can be interpreted, in a consolidated way, according with the following criteria:

Criteria 1: IDTC = 0 => No immediate variations in quantity of transactions of operational processes analyzed. Digital transformation process with cero intensity in immediate term. The insertion of digital technologies did not generate a variation in the quantity of manual tasks.

Criteria 2: IDTC < 0 => Immediate variations in quantity of transactions of operational processes; means falling disruptions in the quantity of manual tasks due to the insertion of digital technologies. Digital transformation process with intensity in immediate term. In this case, digital technologies generated a decrease in the quantity of manual tasks.

Criteria 3: IDTC > 0 => No immediate variations in quantity of transactions of operational processes; means upward disruptions in the quantity of manual tasks due to the insertion of digital technologies. Digital transformation process did not happen. In this case, digital technologies generated the opposite effect: in a immediate term, it generated an increase in the quantity of manual tasks.

Criteria 4: SDTC = 0 => No sustained variations in quantity of transactions of operational processes. Digital transformation process with cero intensity in sustained term. The insertion of digital technologies did not generate a variation in the quantity of manual tasks.

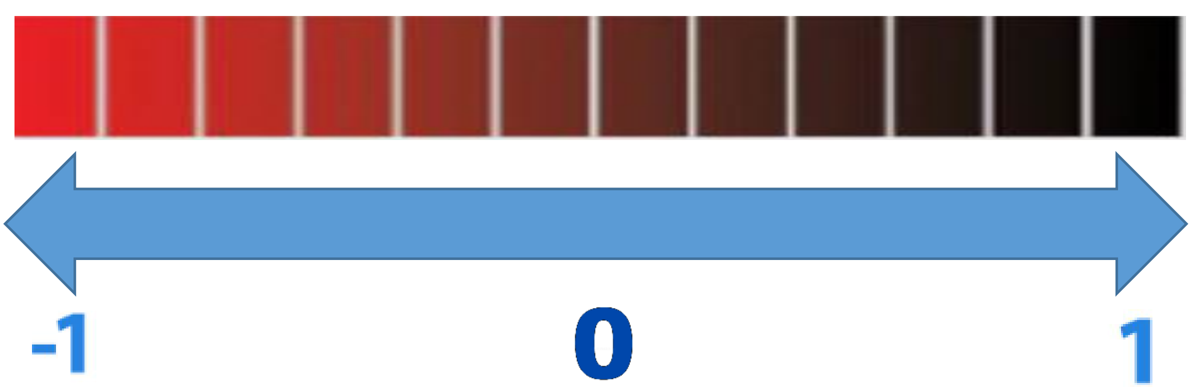
Criteria 5: SDTC < 0 => Sustained variations in quantity of transactions of operational processes; means falling disruptions in the quantity of manual transactions due to the insertion of digital technologies. Digital transformation process with intensity in sustained term. In this case, digital technologies generated a decrease in the quantity of manual tasks.

Criteria 6: SDTC > 0 => No sustained variations in quantity of transactions of operational processes; means upward disruptions in the quantity of manual transactions due to the insertion of digital technologies. Digital transformation process did not happen. In this case, digital technologies generated the opposite effect: in a immediate term, it generated an increase in the quantity of manual tasks.

Immediately after interpreting IDTC and SDTC according with the mentioned criteria, intensity of the DT process can be evaluated for all those results that matched criteria 2 (Immediate term, IDTC) and criteria 5 (Sustained Term, SDTC). For that, the weighted values for both coefficients matching such criteria must be calculated. In those cases, as stated before, insertion of digital technologies generated a decrease in the quantity of manual tasks of certain operational processes in both scenarios (immediate term and sustained term). Thus, Digital transformation intensity can be evaluated based on the quantitative result of both coefficients, because the disruption (decrease) in the quantity of manual tasks is a percent variation.

The following image shows the color pattern used to evaluate DT´s intensity based on quantitative results of both coefficients:

Image 8.5
DT Quantum Model. Color pattern for DT intensity in consolidated evaluation.



To evaluate DT's consolidated intensity (for both coefficients), the following criteria applies:

• If results are larger than cero, means that DT process did not happen because the weighted coefficients showed a consolidated increase in the quantity of manual tasks after the insertion of digital technologies. The farther from cero toward one, the lower intensity of DT process. In some cases, the result could be located beyond one, in cases in which the variation would be bigger than 100%.

• If results are lower than cero, means that DT process indeed happened because the weighted coefficients showed a consolidated decrease in the quantity of manual tasks after the insertion of digital technologies. The farther from cero toward minus one, the higher intensity of DT process.

• If results are cero, means that DT did not happen because there were no variations in the quantity of manual tasks after the insertion of digital technologies.

Third Approach: Potential Savings Estimations

Quantitative results of coefficients (IDTC and SDTC) matching criteria 2 and criteria 5, besides of evaluating DT process intensity, can be used to estimate potential savings in various areas in possible DT projects:

1. Financial resources (investments).
2. Workforce.
3. Time.
4. Technology purchases.
5. Physical storage.

For example, if a IDTC result was -70% (weighted), that number can be used to estimate potential immediate savings of 70% in financial resources, workforce, time, purchases or physical storage in future projects in which the insertion of digital technologies could be involved, due to the real-historic experience.

Therefore, another merit of this methodology is that it provides the chance to assign numeric values to variations in manual tasks due to the insertion of digital technologies in operational processes. These values are the inputs to base a procedure to estimate potential savings prior to develop projects related with Digital Transformation. Hence, these coefficients could also be used as quantitative criteria in the topic of investment projects.

CHAPTER 9:

SIMULATED BUSINESS CASE

General premises

A simulated business case has been designed based on the following general premises:

Table 9.1
DT Quantum Model. Simulated business case. General premises

Organization / Company	Commercial Bank
Core business	Development and housing loans and credit cards.
Quantity of Operational processes evaluated	10
Quantity of months of data collection	24
Operational processes evaluated	Manual Loan Analysis
	Manual Credit Card Analysis
	Documents Signatures
	Physical File Storage
	Physical File Review
	Manual Payment Applications
	Balance Certifications
	Phone Balance Inquiry
	Phone Loan Process Status Inquiry
	Phone Credit Card Process Status Inquiry

Digital technologies insertion

The following table shows the types of digital technologies inserted to each operational process:

Operational processes: actual situation

Table 9.2
DT Quantum Model. Simulated business case. Details of digital technologies insertion process

Operational process	Digital technologies inserted	Month of insertion	Manua task replaced
Manual Loan Analysis	ECM[1] digital forms	7th	Manual documents review
Manual Credit Card Analysis	ECM digital forms	10th	Manual documents review
Documents Signatures	Digital signature software	15th	Ordinary signature
Physical File Storage	ECM digitalization platforms	8th	Physical file storage
Physical File Review	ECM digitalization platforms	10th	Physical file review
Manual Payment Applications	Online payment software	17th	Manual application of payments
Balance Certifications	Corporate digital stamp	8th	Manual certification display and printing
Phone Balance Inquiry	Online inquiry platform	9th	Phone-inbound answers to customers
Phone Loan Process Status Inquiry	Online inquiry platform	6th	Phone-inbound answers to customers
Phone Credit Card Process Status Inquiry	Online inquiry platform	11th	Phone-inbound answers to customers

[1] ECM: Enterprise Content Management software.

Manual Loan Analysis

The employees in charge of executing this operational process perform an analysis of all physical documentation provided by customers, in order to determine if they apply or not to a financial loan.

Depending on the type of loan and the amount of money requested, the process requires specific information from customers.

Usually, customers provide crucial information regarding their net income, short-term debts, current mortgages, fixed assets and labor status. Based on that scenario, the Bank performs a global analysis to apply or deny customer's application.

In this process, customers, typically, show up in person in Bank's offices, request for an analyst in customer service platform and, then, after receiving an explanation about the requisites, they leave in order to collect all requested documentation. Some days later, they return to Bank's offices and provide all necessary documentation in order to start the analysis process. Two weeks later, the correspondent financial analyst communicates to the customer the final decision according with the analysis performed before.

Manual Credit Card Analysis

The employees in charge of executing this operational process perform an analysis of all physical documentation provided by customers, in order to determine if they apply or not to a credit card.

Customers provide crucial information regarding their net income, short-term debts, current mortgages, fixed assets, labor status and details of other credit card previously approved. Based on that scenario, the Bank performs a global analysis to apply or deny customer's application.

In this process, customers, typically, show up in person in Bank's offices, request for an analyst in customer service platform and, then, after receiving an explanation about the requisites, they leave in order to collect all requested documentation. Some days later, they return to Bank's offices and provide all necessary documentation in order to start the analysis process. One week later, the correspondent financial analyst communicates to the customer the final decision according with the analysis performed before.

Documents Signatures

All physical documentation that needs to be signed by managerial levels or board of diectors, has to follow an specific administrative track.

Documentation is generated in operational levels of the Bank. Then, depending on the manager or director that needs to sign the documents, they are sent manually to specific points of contact in diverse areas of the organization. Afterwards, such point of contact receives the documentation, fills a physicall form and then puts all proper documents in a line, ordered by date and hour of reception.

Once the correpondent manager or director signs the documents, they are returned to the point of contact that received it previously. Afterwards, such person contacts the department interested to notify them that the document has been already signed. Finally, a person of the interested department, after the mentioned notification, withdraws the signed documentation. The average duration of this process, depending on the volume of documents, takes from 1-3 business days.

Physical File Storage

All Bank's physical documentation is storaged in large shelfs, located in diverse places of headquarter's building.

All depatments have specific shelfs to storage the documentation. Each department, depending on their functions, builds physical files for every customer, project or specific operational issue.

Everytime a new physical file is generated and needs to be storaged properly, it is transferred to the person in charge of administering the shelf. Such employee receives the file, fills an official form and, then, puts it into the shelf.

Everytime a person of a determined department needs a file to consult it or to update its content, must need to contact directly the correspondent shelf's administrator. Such employee will lend the file to the interested person, with the compromise to return it after a certain period of time. If the file is not returned in time to shelf's administrator, the person who received the file exposes itself to a fine.

The mentioned shelfs occupy an important area of the bank's building, because the organization manages large amounts of documentation.

Physical Files Review

Everytime an employee needs to review a physical file (for meetings with customers, for internal-operational meetings, to follow up issues, etc), he/she needs to contact directly the correspondent shelf's administrator to coordinate a borrow.
The fact of borrowing a physical fiel brings along some relevant risks for the organization as a whole:

1. The complete file could get lost.
2. An employee, in a fradulent way, could steal the complete file.
3. Parts of the file could get lost.
4. The complete file or parts of it could get damaged.

In addition, if an employee is attending a customer in person, and a review of a file is needed, the fact of getting it from the shelf, using it during the meeting and returning it back to the shelf, would take a lot of time.

Another important issue regarding this section is the file-update tasks. Everytime an employee needs to update a file, he/she would need to add the proper documentation to the file. The issue at this point is that nobody at the bank would know that a determined file had been updated; if the file would be used again later in a new meeting, the employee who conducts the meeting would not know that the file was updated before.

Finally, one of the most important issues of this section is that physical files, usually, do not have a back-up in case of disappearance or destruction. If a file gets lost or destroyed, crucial personal-legal-professional documentation from customers would dissapear without recovering anything. This fact would brings along potential legal matters to the bank.

Finally, as mentioned, time spent to review physical files are lengthy and burocratic. Employees and customers face long adminstrative processes to obtain, analyse and return files.

Manual Payment Applications

Everytime a customer that formalized a loan and wants to make a payment to its financial operation, either if it is on time or delayed, must make a bank's deposit and, then, send the the proper supporting document by fax or e-mail, in order to let the bank apply it properly in their system. In the majority of times, customers call the bank immediately after making such deposit, just to let them know that a transaction had been done, in order them to apply it properly into the correspondent database.

The mentioned administrative process involves one or more employees in charge of receiving calls and applying payments manually. When the calls queue is significantly high, the phone-waiting-time is very long for customers who want to notify their payments. This situation generates disconformity and, sometimes, anger. Finally, this issue produces bad customer service from the bank.

Due to the mentioned situation, normally, a payment is applied properly within a time range of 1-2 business days. Not so often, a payment is applied the same day the correspondent deposit is made. Often, delays in payment applications produces imbalances in interests calculations of the financial operations of customers.

As as result of the large quantity of daily deposits, the organization utilizes two or three employees to check closely the bank's account in which customers make the deposits.
Finally, an important annotation in this process is the high probaility of human errors at the moment of a manual application of a payment. If an error is detected, the involved employee must reverse it, and this, consequently, brings along a chain of adjustment transactions in the system that could end in calculation´s errors.

Balance Certifications

Is common that customers request documents in which the Bank certifies their payment history and their balance. To do so, customers can arrive to the Bank to request such documents, or they can make a phone call to complete the request. Once customers formalizes the request (either personally or by phone), bank's employees fill a digital form into the system and, finally, print the proper certification.
This process takes a few minutes, but customers have to arrive to bank's offices or make a phone call to complete the request and obtain the correspondent certification.

Phone Balance Inquiry

Is usual that customers call Bank's Department of Loans to ask for their balance or to confirm that their payment history is up to date.
Due to the high quantity of loans formalized by the bank, there is a large quantity of customes with active financial operations. Therefore, this generates a daily high volume of incoming

calls, issue that obligates the bank to assign a lot of employees to take those calls. To do that, the bank has organized a complete Customer Service Department with its correspondent administrative structure.
During the last months, the Bank has been experimenting a lot of lost calls, long waiting times and bad customer service due to the high volume of incoming calls.

Phone Loan Process Status Inquiry

Just as the “Phone Balance Inquiry” process, this one is attended by the Customer Service Department.

Everytime a customer formalizes a loan request, the correspondent administrative procedure takes around two weeks to be completed. In the meantime, a lot of customers call the Bank asking for the status of such process. This issue generates a daily high volume of incoming calls, obligating the bank to assign a lot of employees to take those calls.
During the last months, the Bank has been experimenting a lot of lost calls, long waiting times and bad customer service due to the high volume of incoming calls.

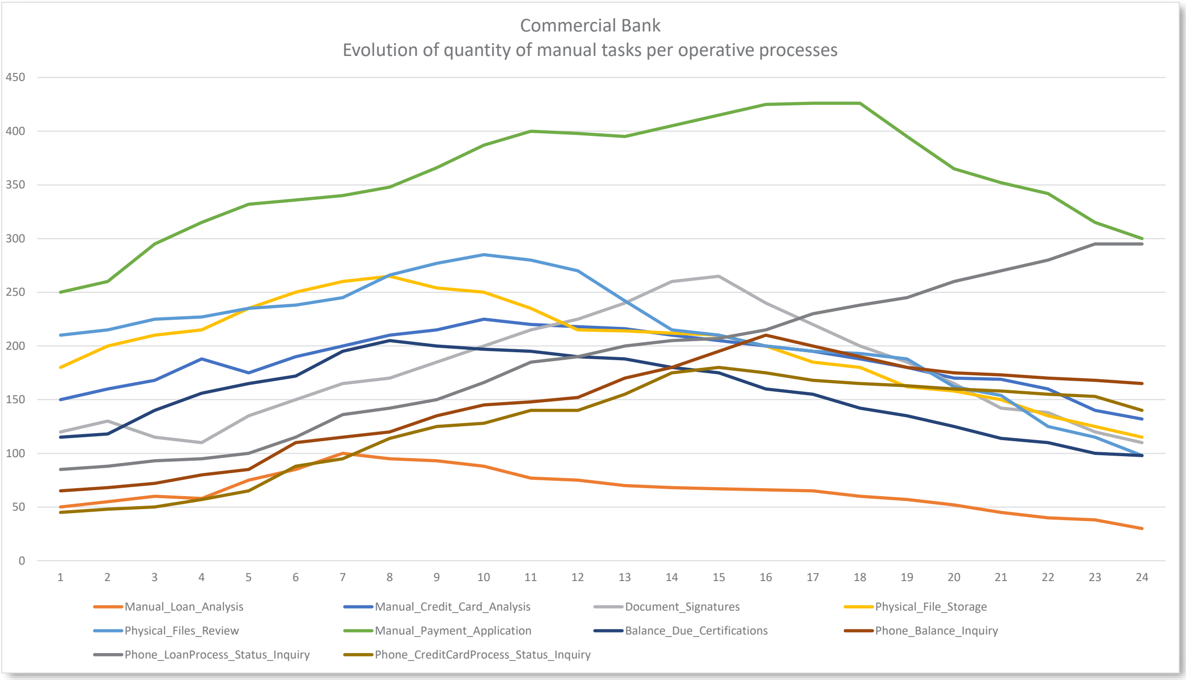
Phone Credit Card Process Status Inquiry

Just as the lat two processes, this one is attended by the Customer Service Department.
Everytime a customer formalizes a credit card request, the correspondent administrative procedure takes around one week to be completed. In the meantime, a lot of customers calls the Bank asking for the status of such process. This issue generates a daily high volume of incoming calls, obligating the bank to assign a lot of employees to take those calls.
During the last months, the Bank has been experimenting a lot of lost calls, long waiting times and bad customer service due to the high volume of incoming calls.

Operational processes: evolution of quantity of manual tasks

Image 9.1 shows the evolution of the quantity of manual tasks durint the 24-month period of data collection.

Image 9.1
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks per operational process



Remarks:
1. The X axis shows the 24-month time range of data collection.
2. The Y axis shows the quantiy of manual tasks.

Image 9.2 shows the complete detail of the quantity of manual tasks per Operational process, within the 24-month of data collection time range:

Image 9.2
DT Quantum Model. Simulated business case. Quantity of manual tasks per operational process

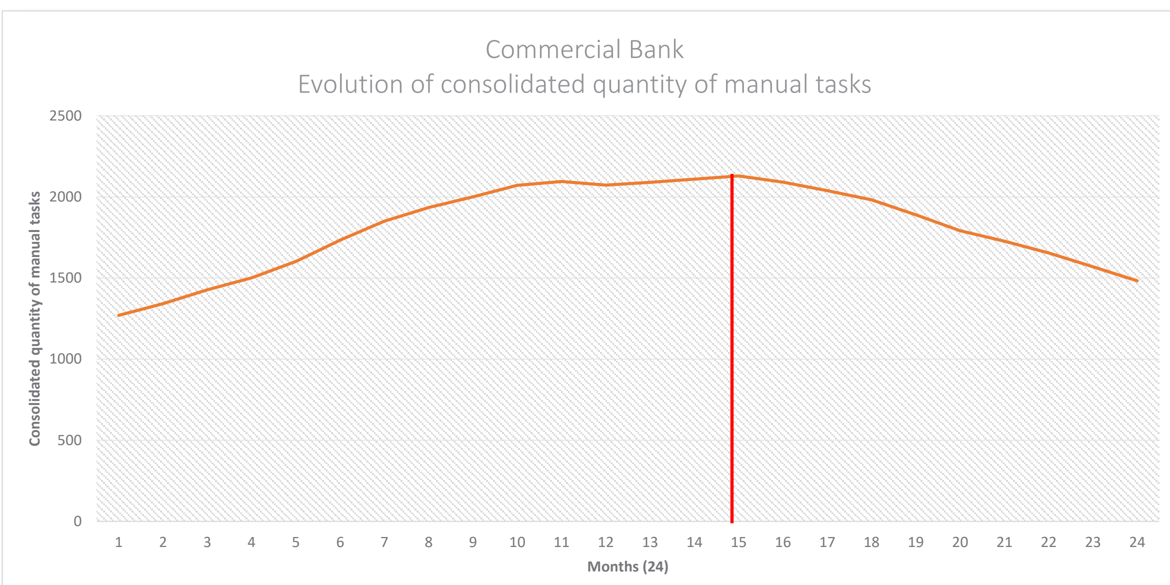
Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Remarks:

1. The boxes filled with yellow shows the exact moment of the insertion of digital technologies per operational process.
2. In consolidated terms, Commercial Bank collected a total of 43.459 manual tasks.

In addition, image 9.3 shows the evolution of the consolidated quantity of manual tasks within the 24 months of data collection:

Image 9.3
DT Quantum Model. Simulated business case. Consolidated quantity of manual tasks



Remarks:

1. Since the 15th month, in consolidated terms, the quantity of manual tasks began to decrease due to the insertion of digital technologies. Precisely, due to the contents of Image 9.2, digital technologies were inserted within a defined time range from the 6th month up to the 17th month, in the different operational processes. This situation generated that, since the 15th month, the quantity of consolidated manual tasks of all operational processes began to decrease.

Operational processes:
situation after the insertion of digital technologies

As mentioned in the last section, some digital technologies were inserted into all bank's operational processes. Those new technologies were inserted in different moments in time. Due to such insertion, an effect or impact was generated in every single process, in terms of an increase or a decrease in the quantity of manual tasks. These variations will originate the type of disruption (as explained in Chapter 6) and the calculations of the correspondent coefficients. The following sections will explain, in detail, the particular situation generated in every operational process, due to the mentioned insertion.

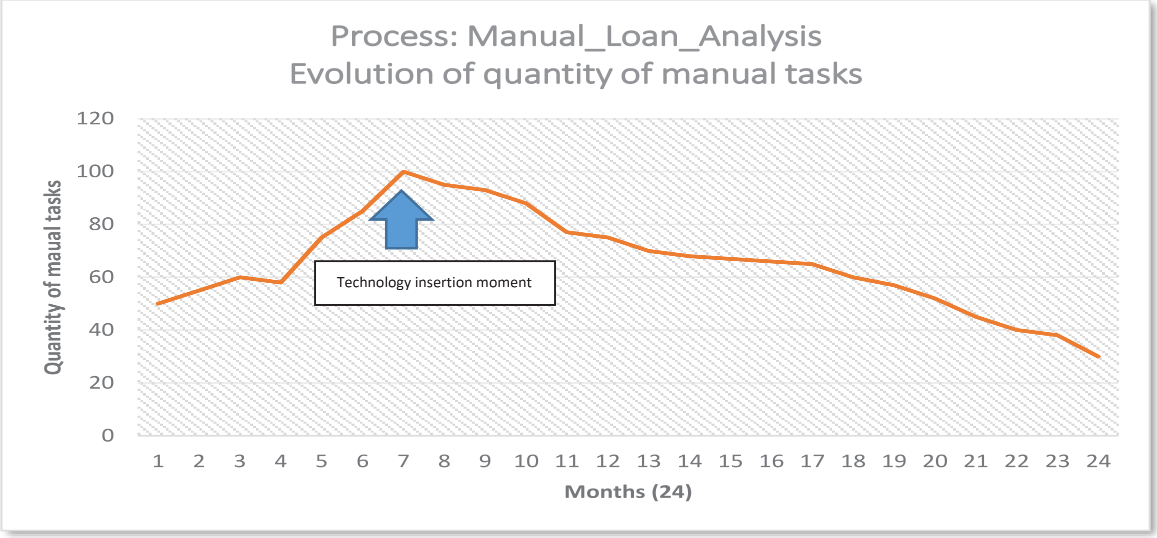
Manual Loan Analysis

In this process, an ECM (Enterprise Content Management) digital form was inserted in order to automate the loans's request analysis of every customer. In this case, the manual work of studying all physical documention was replaced by a digital tool in which employees enter all crucial information and digitalize all paper-based documents. Therefore, all manual analysis per customer was replaced by an automatic work in digital forms. At the end of the analysis process, the final product expected would be a summary-report that can be sent to supervisors and managerial levels with the correspondent final decision of each case.
Image 9.4 shows the evolution of the quantity of manual tasks in this process, and Image 9.5 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.4
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Manual Loan Analysis

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.5
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Manual Loan Analysis



The insertion of the ECM digital form in the 7th month generated a immediate disruption of 5 manual tasks, and a variation of 70 tasks up to the final month of the data collection.

Thus, is clear that the curve showed by Image 9.5 displays a decrease since the 7th month, and its tendency was sustained until the final month (24th).

Table 9.3 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.3
DT Quantum Model. Simulated business case. Manual Loan Analysis process. DTCI and DTCS results

Detail	Result
Highest value	100
Immediate value	95
Final value	30
Digital Transformation Coefficient Immediate	**-5%**
Digital Transformation Coefficient Sustained	**-70%**

Manual Credit Card Analysis

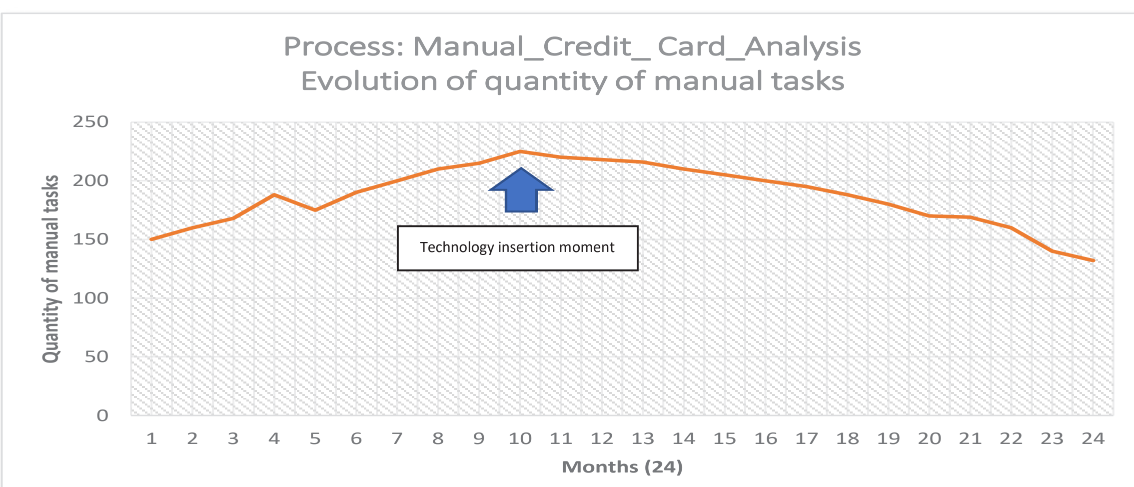
In this process, an ECM (Enterprise Content Management) digital form was inserted in order to automate the credit card's request analysis of every customer. In this case, the manual work of studying all physical documention was replaced by a digital tool in which employees enter all crucial information and digitalize all paper-based documents. Therefore, all manual analysis per customer was replaced by an automatic work in digital forms. At the end of the analysis process, the final product expected would be a summary-report that can be sent to supervisors and managerial levels with the correspondent final decision of each case.

Image 9.6 shows the evolution of the quantity of manual tasks in this process, and Image 9.7 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.6
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Manual Credit Card Analysis

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	1569
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	4484
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	4205
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	4815
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	5070
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	8588
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	3730
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	3471
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	4485
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	3042
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.7
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Manual Credit Card Analysis



The insertion of the ECM digital form in the 10th month generated a immediate disruption of 5 manual tasks, and a variation of 93 tasks up to the final month of the data collection.

Thus, is clear that the curve show by Image 9.7 displays a decrease since the 10th month, and its tendency was sustained until the final month (24th).

Table 9.4 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.4
DT Quantum Model. Simulated business case. Manual Credit Analysis process. DTCI and DTCS results

Detail	Result
Highest value	225
Immediate value	220
Final value	132
Digital Transformation Coefficient Immediate	**-2.2%**
Digital Transformation Coefficient Sustained	**-41.33%**

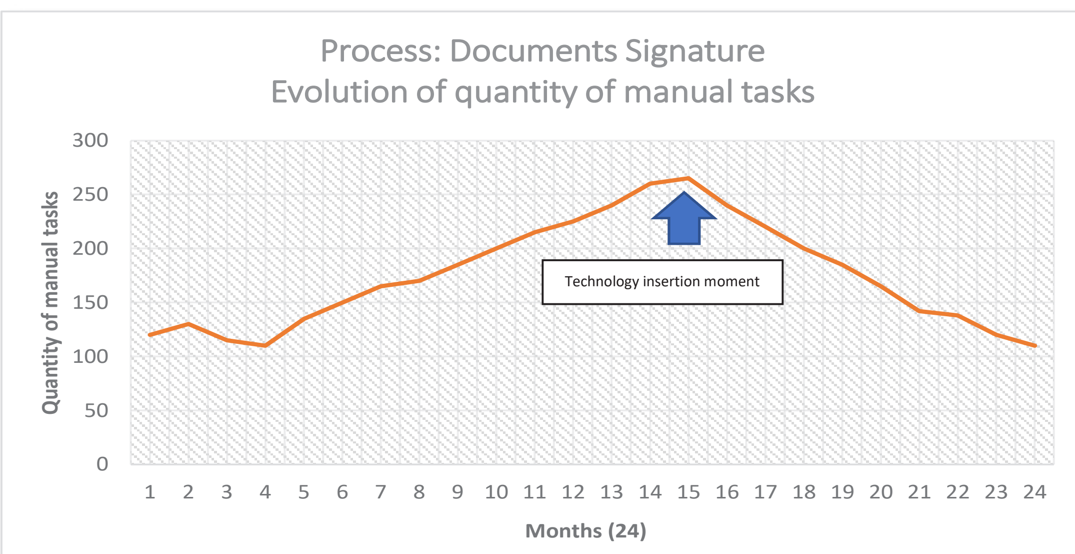
Documents Signatures

In this process, a digital signature software was inserted in order to automate the signature process of crucial documentation. In this case, the manual signature is not longer needed, and neither the burocratic process in which employees request the signatures from managers and directors. The new technology implemented would allow people to sign documentation in a digital way by themselves, replacing the usage of paper and long administrative processes. Image 9.8 shows the evolution of the quantity of manual tasks in this process, and Image 9.9 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.8
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Documents Signatures

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.9
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Documents Signatures



The insertion of the Digital Signature Technology in the 15th month generated a immediate disruption of 25 manual tasks, and a variation of 155 tasks up to the final month of data collection.

Thus, is clear that the curve show by Image 9.9 shows a decrease since the 15th month, and its tendency was sustained until the final month (24th).

Table 9.5 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.5
DT Quantum Model. Simulated business case. Documents Signatures process. DTCI and DTCS results

Detail	Result
Highest value	265
Immediate value	240
Final value	110
Digital Transformation Coefficient Immediate	**-9.43%**
Digital Transformation Coefficient Sustained	**-58.49%**

Physical File Storage

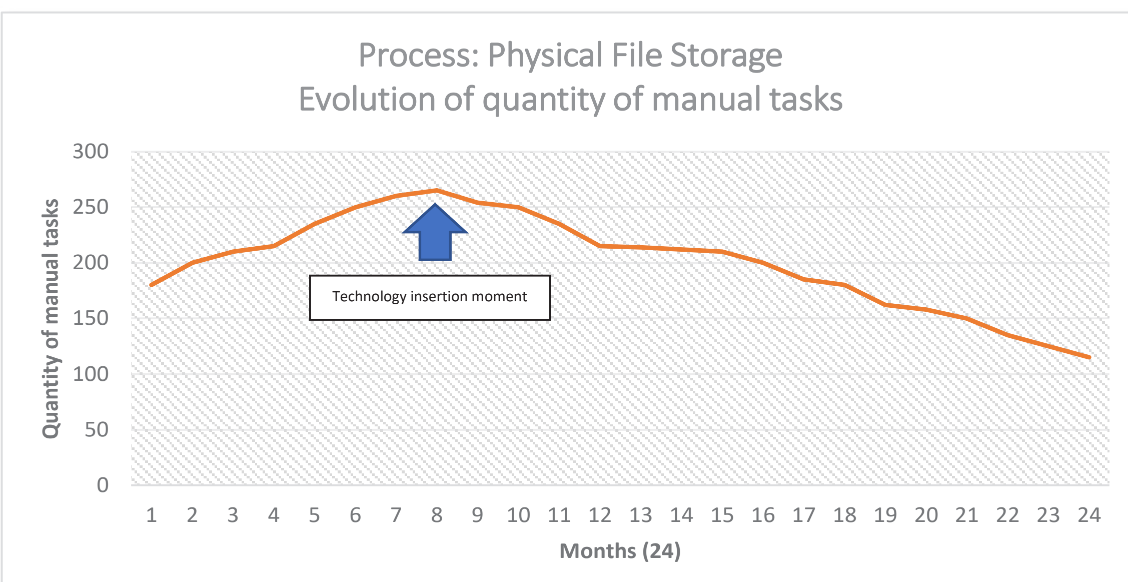
In this process, an ECM digitalization platform was inserted in order to automate documentation management. In this case, the physical documents are scanned and transformed into digital images in a consolidated platform. By such usage, time spent to store and guard files has decreased dramatically. Large storage rooms and physical shelfs are not needed anymore, reducing large amounts of monthly financial costs.

Image 9.10 shows the evolution of the quantity of manual tasks in this process, and Image 9.11 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.10
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Physical File Storage

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.11
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Physica File Storage



The insertion of the ECM Digitalization Platform in the 8th month generated a immediate disruption of 11 manual tasks, and a variation of 150 tasks up to the final month of data collection.

Thus, is clear that the curve show by Image 9.11 shows a decrease since the 8th month, and its tendency was sustained until the final month (24th).

Table 9.6 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.6
DT Quantum Model. Simulated business case. Physical File Storage process. DTCI and DTCS results

Detail	Result
Highest value	265
Immediate value	254
Final value	115
Digital Transformation Coefficient Immediate	**-4.15%**
Digital Transformation Coefficient Sustained	**-56.60%**

Physical File Review

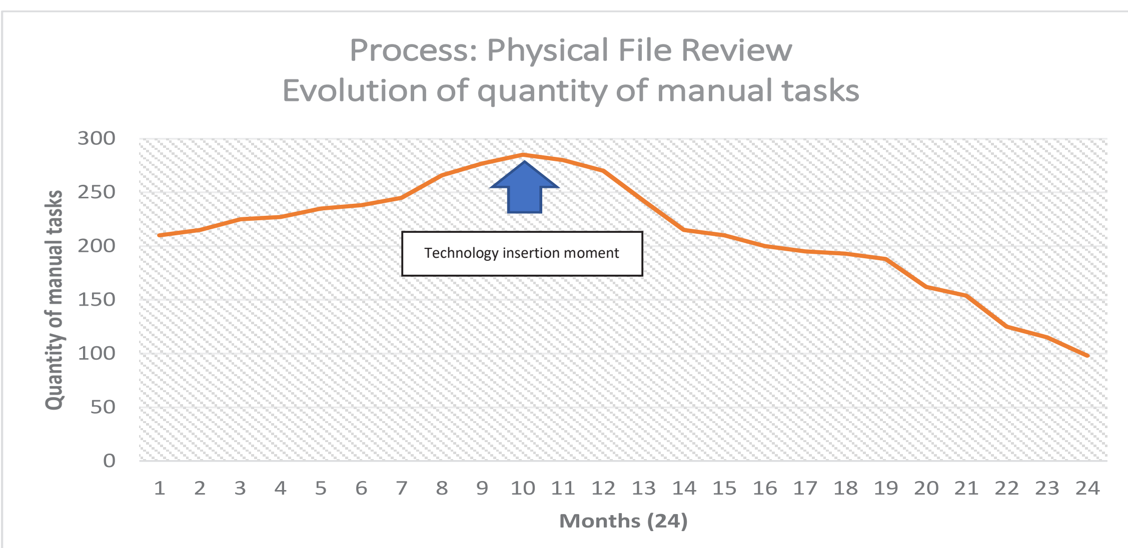
In this process, an ECM digitalization platform was inserted in order to automate documentation management. In this case, the physical documents are scanned and transformed into digital images in a consolidated platform. By such usage, time spent to consult files in front of customers or internal employees has decreased dramatically. Long waiting times in meetings and long response times in administrative processes has also decreased.

Image 9.12 shows the evolution of the quantity of manual tasks in this process, and Image 9.13 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.12
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Physical File Review

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.13
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Physical File Review



The insertion of the ECM Digitalization Platform in the 10th month generated a immediate disruption of 5 manual tasks, and a variation of 187 tasks up to the final month of data collection.

Thus, is clear that the curve show by Image 9.13 shows a decrease since the 10th month, and its tendency was sustained until the final month (24th).

Table 9.7 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.7
DT Quantum Model. Simulated business case. Physical File Review process. DTCI and DTCS results

Detail	Result
Highest value	285
Immediate value	280
Final value	98
Digital Transformation Coefficient Immediate	**-1.75%**
Digital Transformation Coefficient Sustained	**-65.61%**

Manual Payment Applications

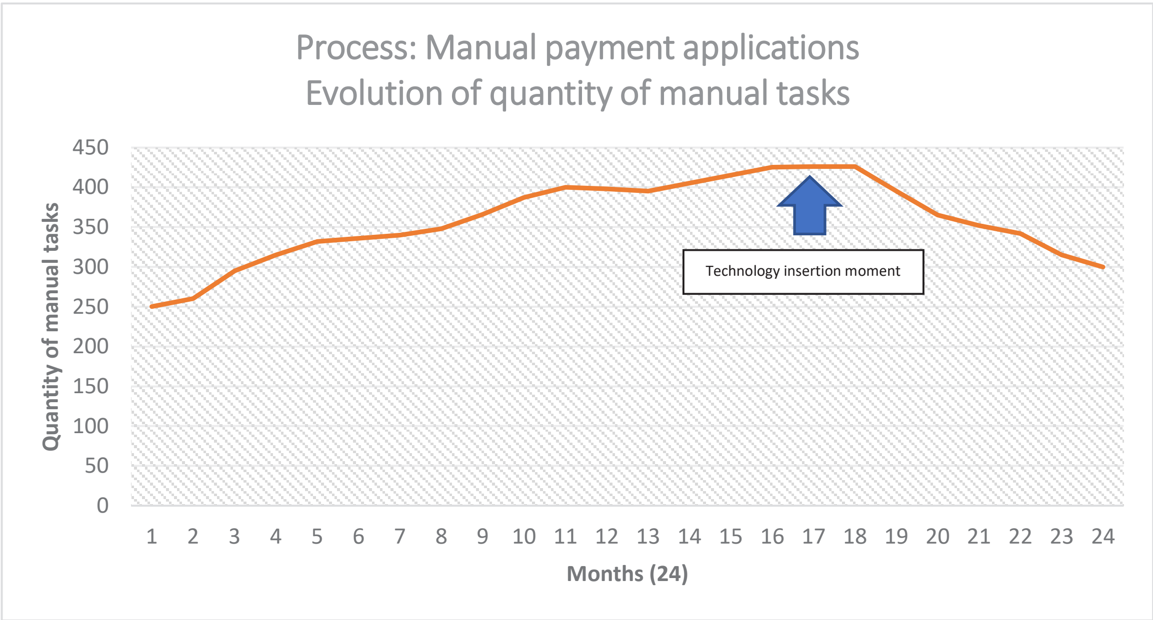
In this process, an online payment software was inserted in order to automate the manual payments application. In this case, the mentioned manual task was replaced by an online application in which customers apply their payments automatically. By such usage, long time spent by employees applying each payment manually is not needed anymore, because they are applied automatically online. In addition, quantity of incoming phone calls in which customers ask for payment applications has also decreased dramatically.

Image 9.14 shows the evolution of the quantity of manual tasks in this process, and Image 9.15 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.14
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Manual Payment Applications

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.15
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Manual Payment Applications



The insertion of the ECM Digitalization Platform in the 177h month did not generate an immediate disruption in manual tasks, but generated a sustained variation of 126 tasks up to the final month of data collection.

Table 9.8 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.8
DT Quantum Model. Simulated business case. Manual Payments Applications process. DTCI and DTCS results

Detail	**Result**
Highest value	426
Immediate value	426
Final value	300
Digital Transformation Coefficient Immediate	**0%**
Digital Transformation Coefficient Sustained	**-29.58%**

Balance Certifications

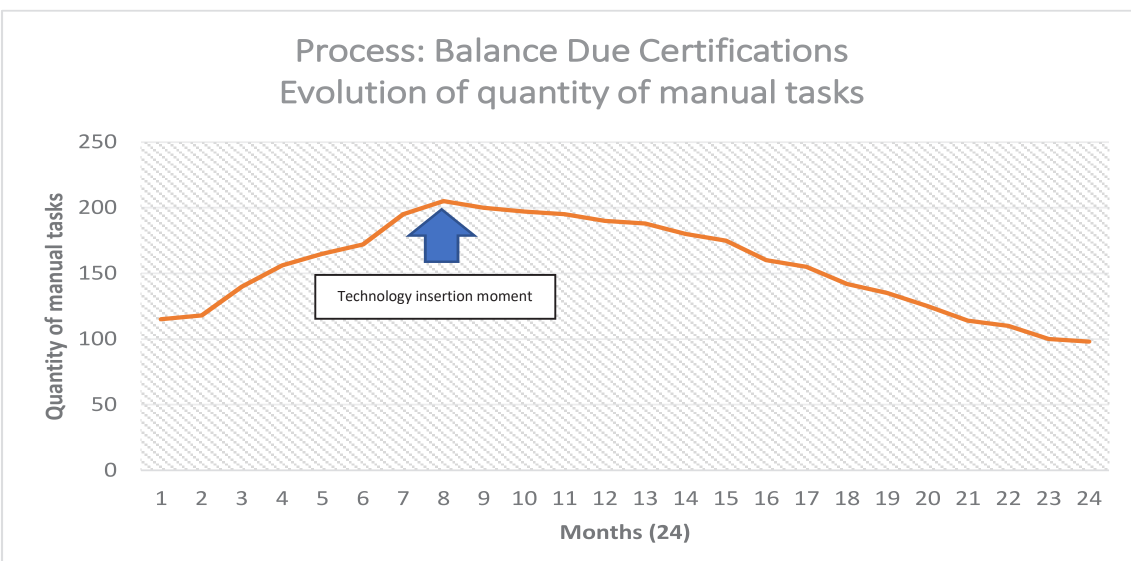
In this process, a corporate digital stamp application was inserted in order to automate the delivery of balance due certifications to customers. In this case, the manual task in which employees download, print and delivery physical certifications to customers, was replaced by an online application in which customers enter to bank's webpage to download by themselves such document already stamped. By such usage, long time spent by employees applying each payment manually is not needed anymore, because they are applied automatically online. In addition, quantity of incoming phone calls in which customers ask for payment applications has also decreased dramatically.

Image 9.16 shows the evolution of the quantity of manual tasks in this process, and Image 9.17 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.16
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Balance Certifications

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.17
DT Quantum Model. Simulated business case. Evolution of quantity of manual tasks, process of Balance Certifications



The insertion of the ECM Digitalization Platform in the 8th month generated an immediate disruption of 5 manual tasks, and generated a sustained variation of 107 tasks up to the final month of data collection.

Table 9.9 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.9
DT Quantum Model. Simulated business case. Balance Certifications process. DTCI and DTCS results

Detail	Result
Highest value	205
Immediate value	200
Final value	98
Digital Transformation Coefficient Immediate	**-2.44%**
Digital Transformation Coefficient Sustained	**-52.20%**

Phone Balance Inquiry

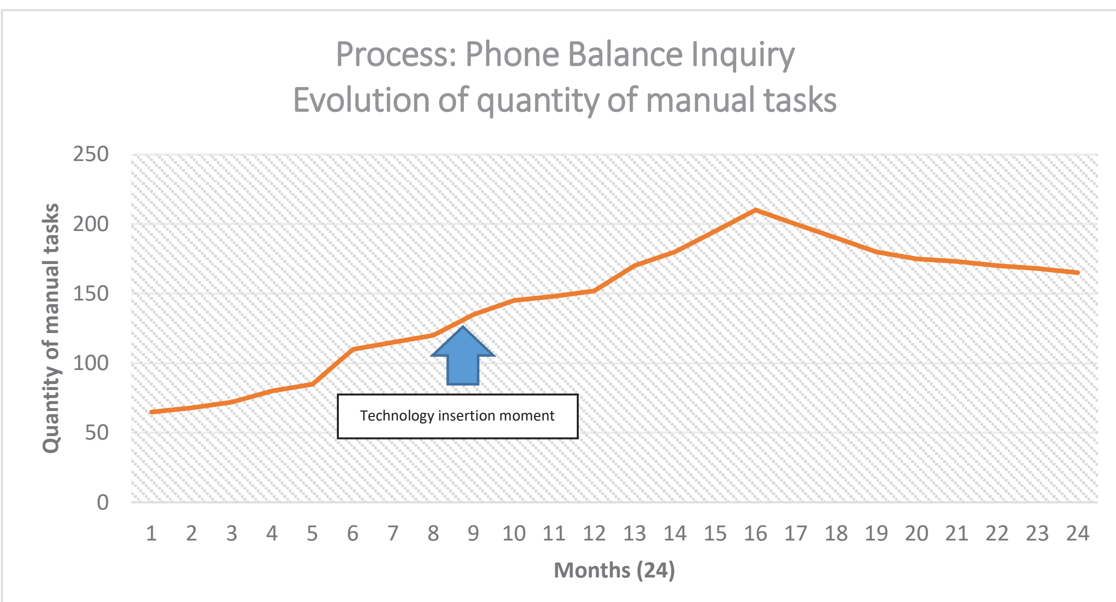
In this process, an online inquiry platform application was inserted in order to automate the answering process due to incoming calls made by customers. In this case, the manual task in which employees answer phone calls made by customers asking for their balance, was replaced by an online application in which customers enter to bank's webpage to made an automatic inquiry by themselves. By such usage, long time spent by employees answering the incoming calls has decreased dramatically.

Image 9.18 shows the evolution of the quantity of manual tasks in this process, and Image 9.19 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.18
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Phone Balance Inquiry

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.19
DT Quantum Model. Simulated business case. Evolution o f quantity of manual tasks, process of Phone Balance Inquiry



The insertion of the online inquiry platform in the 9th month did not generate an immediate disruption in manual tasks, and neither a sustained variation, due to the fact that final number of quantity of manual tasks, at the 24th month was 165.

Table 9.10 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.10
DT Quantum Model. Simulated business case. Phone Balance Inquiry process. DTCI and DTCS results

Detail	Result
Highest value	135
Immediate value	145
Final value	165
Digital Transformation Coefficient Immediate	**7.41%**
Digital Transformation Coefficient Sustained	**22.22%**

In this specific case, an exception must be performed in coefficient's calculations and analysis.

Due to the fact that the mentioned digital techology was inserted in the 9th month, it did not generate an immediate decrease in the quantity of manual tasks, and the maximum value was experimented until the 16th month and, since then, a decrease happened until the last month of analysis, in real terms, a digital transformation process did not happen in this process despite of the circumstance that the curve, since the 16th month, experimented a decrease in the quantity of manual tasks.

This particular situation happens because, at the moment of the insertion of the online inquiry platform in the 9th month, there were 135 manual tasks collected. The immediate month registered 145 manual tasks. At the end of the time range of analysis (month 24th), there were 165 manual tasks collected. So, in a immediate and sustained terms, no digital transformation happened.

Hence, in this particlar case, in order to develop the calculation of the coefficients, the highest value (16th month, 210 manual tasks) of the dataset must be replaced by the month in which the digital transformation was inserted (6th month, 135 manual tasks). From that number, there would be a new immediate value (145 manual tasks). The final value should keep constant.

The results of the coefficients, due to the mentioned scenario, displayed a positive result for both coefficients. That means that a digital transformation process did not happen.
Finally, it is quiet important to mention that, the cited exception must be applied in all cases with the following conditions:

1. There is no immediate decrease in the quantity of manual tasks at the moment of the insertion of digital technologies.
2. There is a maximum value of quantity of manual tasks, but it is located periods after the moment of insertion of the digital technology.

Phone Loan Process Status Inquiry

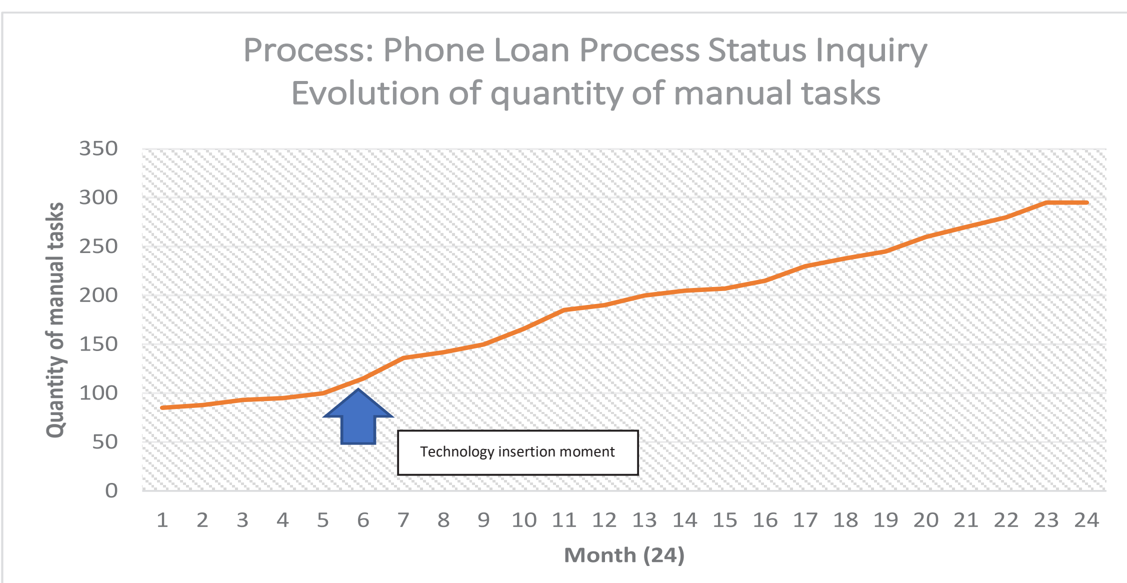
In this process, an online inquiry platform application was inserted in order to automate the answering process due to incoming calls made by customers. In this case, the manual task in which employees answer phone calls made by customers asking for the status of their loan request, was replaced by an online application in which customers enter to bank's webpage to made an automatic inquiry by themselves. By such usage, long time spent by employees answering the incoming calls has decreased dramatically.

Image 9.20 shows the evolution of the quantity of manual tasks in this process, and Image 9.21 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.20
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Phone Loan Process Status Inquiry

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.21
DT Quantum Model. Simulated business case. Evolution o f quantity of manual tasks, process of Phone Loan Process Status Inquiry



The insertion of the online inquiry platform in the 6th month did not generate an immediate disruption in manual tasks, and neither a sustained variation, due to the fact that final number of quantity of manual tasks increased up to a maximum value of 295 tasks in the 23th month and, since then, continued constant to 295 in the 24 th month.

Table 9.11 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.11
DT Quantum Model. Simulated business case. Phone Loan Process Status Inquiry process. DTCI and DTCS results

Detail	Result
Highest value	115
Immediate value	136
Final value	295
Digital Transformation Coefficient Immediate	**18.26%**
Digital Transformation Coefficient Sustained	**156.52%**

In this specific case, and as same as the last operational process, an exception must be performed in coefficient's calculations and analysis.

Due to the fact that the mentioned digital techology was inserted in the 6th month, it did not generate an immediate decrease in the quantity of manual tasks, and the maximum value was experimented until the 23th month, in real terms, a digital transformation process did not happen in this operational process.
This particular situation happens because, at the moment of the insertion of the online inquiry platform in the 6th month, there were 115 manual tasks collected. The after-immediate month registered 136 manual tasks. At the end of the time range of analysis (month 24th), there were 295 manual tasks collected. So, in a immediate and sustained terms, no digital transformation happeneded.

Therefore, in this particlar case, in order to develop the calculation of the coefficients, the highest value (23th month, 295 manual tasks) of the data range must be replaced by the month in which the digital transformation was inserted (6th month, 115 manual tasks). From that number, there would be a new immediate value (136 manual tasks). The Final Value should keep constant.

The results of the coefficients, due to the mentioned scenario, displayed a positive result for both coefficients. That means that, in real terms, a digital transformation process did not happen.

Finally, it is quiet important to mention that, the mentioned exception must be applied in all cases with the following conditions:

1. There is no immediate decrease in the quantity of manual tasks at the moment of the insertion of digital technologies.
2. There is a maximum value of quantity of manual tasks, but it is located periods after the moment of insertion of the digital technology.

Phone Credit Card Process Status Inquiry

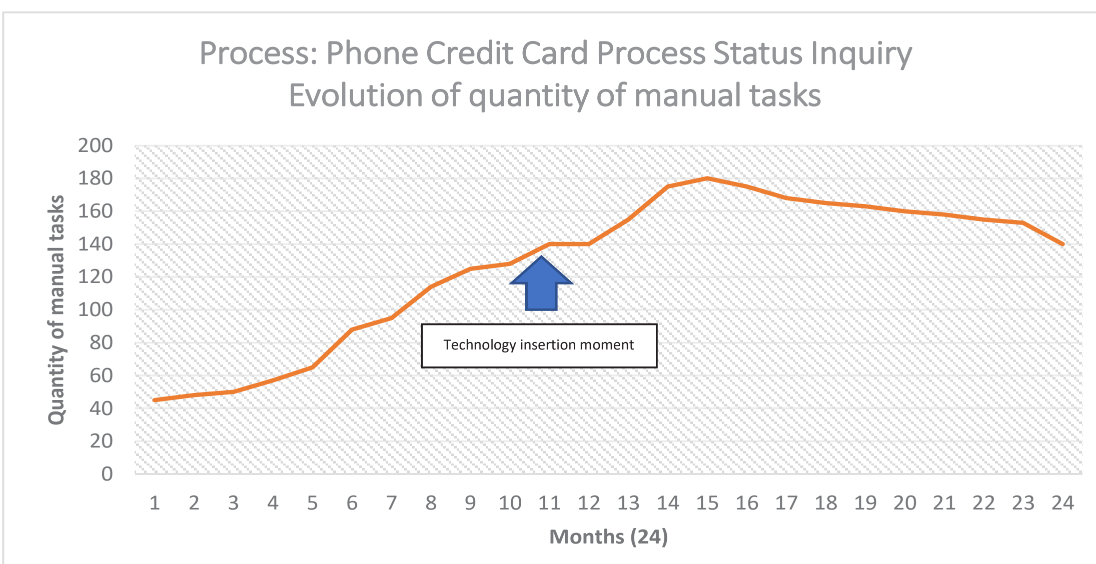
In this process, an online inquiry platform application was inserted in order to automate the answering process due to incoming calls made by customers. In this case, the manual task in which employees answer phone calls made by customers asking for the status of their credit card request, was replaced by an online application in which customers enter to bank's webpage to made an automatic inquiry by themselves. By such usage, long time spent by employees answering the incoming calls has decreased dramatically.

Image 9.22 shows the evolution of the quantity of manual tasks in this process, and Image 9.23 shows the visualization plot in which the expected effect of the insertion of digital technologies is displayed:

Image 9.22
DT Quantum Model. Simulated business case. Quantity of manual tasks, process of Phone Credit Card Process Status Inquiry

Operative_Process	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Total
Manual_Loan_Analysis	50	55	60	58	75	85	100	95	93	88	77	75	70	68	67	66	65	60	57	52	45	40	38	30	**1569**
Manual_Credit_Card_Analysis	150	160	168	188	175	190	200	210	215	225	220	218	216	210	205	200	195	188	180	170	169	160	140	132	**4484**
Documents_Signatures	120	130	115	110	135	150	165	170	185	200	215	225	240	260	265	240	220	200	185	165	142	138	120	110	**4205**
Physical_File_Storage	180	200	210	215	235	250	260	265	254	250	235	215	214	212	210	200	185	180	162	158	150	135	125	115	**4815**
Physical_Files_Review	210	215	225	227	235	238	245	266	277	285	280	270	242	215	210	200	195	193	188	162	154	125	115	98	**5070**
Manual_Payment_Applications	250	260	295	315	332	336	340	348	366	387	400	398	395	405	415	425	426	426	395	365	352	342	315	300	**8588**
Balance_Certifications	115	118	140	156	165	172	195	205	200	197	195	190	188	180	175	160	155	142	135	125	114	110	100	98	**3730**
Phone_Balance_Inquiry	65	68	72	80	85	110	115	120	135	145	148	152	170	180	195	210	200	190	180	175	173	170	168	165	**3471**
Phone_LoanProcess_Status_Inquiry	85	88	93	95	100	115	136	142	150	166	185	190	200	205	207	215	230	238	245	260	270	280	295	295	**4485**
Phone_CreditCardProcess_Status_Inquiry	45	48	50	57	65	88	95	114	125	128	140	140	155	175	180	175	168	165	163	160	158	155	153	140	**3042**
Total	**1270**	**1342**	**1428**	**1501**	**1602**	**1734**	**1851**	**1935**	**2000**	**2071**	**2095**	**2073**	**2090**	**2110**	**2129**	**2091**	**2039**	**1982**	**1890**	**1792**	**1727**	**1655**	**1569**	**1483**	**43459**

Image 9.23
DT Quantum Model. Simulated business case. Evolution o f quantity of manual tasks, process of Phone Credit Card Process Status Inquiry



The insertion of the online inquiry platform in the 11th month did not generate an immediate disruption in manual tasks, and neither a sustained variation, due to the fact that final number of quantity of manual tasks increased up to a maximum value of 180 tasks in the 15th month and, since then, such variable experimented a sustained decrease until the 24 th month.

Table 9.12 shows the results for the DTCI and DTCS coefficients for this process:

Table 9.12
DT Quantum Model. Simulated business case. Phone Credit Card Process Status Inquiry process.
DTCI and DTCS results

Detail	Result
Highest value	140
Immediate value	140
Final value	140
Digital Transformation Coefficient Immediate	**0%**
Digital Transformation Coefficient Sustained	**0%**

In this specific case, and as same as the last operational process, an exception must be performed in coefficient's calculations and analysis.

Due to the fact that the mentioned digital techology was inserted in the 11th month, it did not generate an immediate decrease in the quantity of manual tasks, and the maximum value was experimented until the 15th month, in real terms, a digital transformation process did not happen in this operational process.

This particular situation happens because, at the moment of the insertion of the online inquiry platform in the 11th month, there were 140 manual tasks collected. The after-immediate month registered 140 manual tasks. At the end of the time range of analysis (month 24th), there were 140 manual tasks collected. So, in a immediate and sustained terms, no digital transformation happeneded.

Thus, in this particlar case, in order to develop the calculation of the coefficients, the highest value (15th month, 180 manual tasks) of the data range must be replaced by the month in which the digital transformation was inserted (11th month, 140 manual tasks). From that number, there would be a new immediate value (140 manual tasks). The Final Value kept constant in 140.

The results of the coefficients, due to the mentioned scenario, displayed a result of cero for both coefficients. That means that, in real terms, a digital transformation process did not happen.

Finally, it is quiet important to mention that, the mentioned exception must be applied in all cases with the following conditions:

1. There is no immediate decrease in the quantity of manual tasks.
2. There is a maximum value of quantity of manual tasks, but it is located periods after the moment of insertion of the digital technology.

Operational processes: consolidated analysis

Immediate term

After performing all individual calculations and analysis for every single operational processes, a consolidated examination can be executed, in order to display the weighted coefficients for the immediate term. Image 9.24 shows the consolidated results for the ten operational processes:

Table 9.13
DT Quantum Model. Simulated business case. Consolidated results. DTCI and DTCS coefficients

Operative_Process	Highest value	Immediate Value	Final Value	DTCI	DTCS
Manual_Loan_Analysis	100	95	30	-5,00%	-70,00%
Manual_Credit_Card_Analysis	225	220	132	-2,22%	-41,33%
Documents_Signatures	265	240	110	-9,43%	-58,49%
Physical_File_Storage	265	254	115	-4,15%	-56,60%
Physical_Files_Review	285	280	98	-1,75%	-65,61%
Manual_Payment_Applications	426	426	300	0,00%	-29,58%
Balance_Due_Certifications	205	200	98	-2,44%	-52,20%
Phone_Balance_Inquiry	135	145	165	7,41%	22,22%
Phone_LoanProcess_Status_Inquiry	115	136	295	18,26%	156,52%
Phone_CreditCardProcess_Status_Inquiry	140	140	140	0,00%	0,00%
Consolidated weighted coefficients				**0,07%**	**-19,51%**

Remarks:

1. In the immediate term, the DTCI coefficient had a result of 0.07%. That means that the weighted variation was of 0.07% due to the insertion of a wide variety of digital technologies in all ten operational processes.
2. The result of 0.07% reflects a positive number (very close to cero). Thus, this coefficient reproduces a scenario in which digital transformation did not happen.
3. Finally, this result could be considered as a fact that the bank, due to the insertion of digital technologies, did not experimented a digital transformation process in an immediate term according to the color pattern criteria because it was close to cero.

Sustained term

After performing all individual calculations and analysis for every singre operational processes, a consolidated examination can be executed, in order to display the werighed coefficients for the sustained term. Image 9.25 shows the consolidated results for the ten operational processes:

Table 9.14
DT Quantum Model. Simulated business case. Consolidated results. DTCI and DTCS coefficients

Operative_Process	Highest value	Immediate Value	Final Value	DTCI	DTCS
Manual_Loan_Analysis	100	95	30	-5,00%	-70,00%
Manual_Credit_Card_Analysis	225	220	132	-2,22%	-41,33%
Documents_Signatures	265	240	110	-9,43%	-58,49%
Physical_File_Storage	265	254	115	-4,15%	-56,60%
Physical_Files_Review	285	280	98	-1,75%	-65,61%
Manual_Payment_Applications	426	426	300	0,00%	-29,58%
Balance_Due_Certifications	205	200	98	-2,44%	-52,20%
Phone_Balance_Inquiry	135	145	165	7,41%	22,22%
Phone_LoanProcess_Status_Inquiry	115	136	295	18,26%	156,52%
Phone_CreditCardProcess_Status_Inquiry	140	140	140	0,00%	0,00%
Consolidated weighted coefficients				**0,07%**	**-19,51%**

Remarks:

1. In the sustained term, the DTCS coefficient had a result of -19.51%. That means that the weighted variation was of -19.51% due to the insertion of a wide variety of digital technologies in all ten operational processes.
2. The result of -19.51% reflects a negative number. Therefore, this coefficient reproduces a scenario in which digital transformation certainly happened.
3. Finally, this result could be considered as a fact that the bank, due to the insertion of digital technologies, experimented a digital transformation process in a sustained term; in addition, such process was medium-intense according to the color pattern criteria because it was less than cero.

Final results: proposed approaches

As mentioned in the foreword, DT Quantum Model proposed calculations and analysis to evaluate results in three approaches:

1. First approach: coefficients results.
2. Second approach: estimate intensity of the digital transformation process based in coefficients results.
3. Third approach: potential estimated savings for the organization in some key areas for future DT projects, based in coefficients results.

First approach

Image 9.26 shows the results for each Operational processes and the consolidated weighed coefficients:

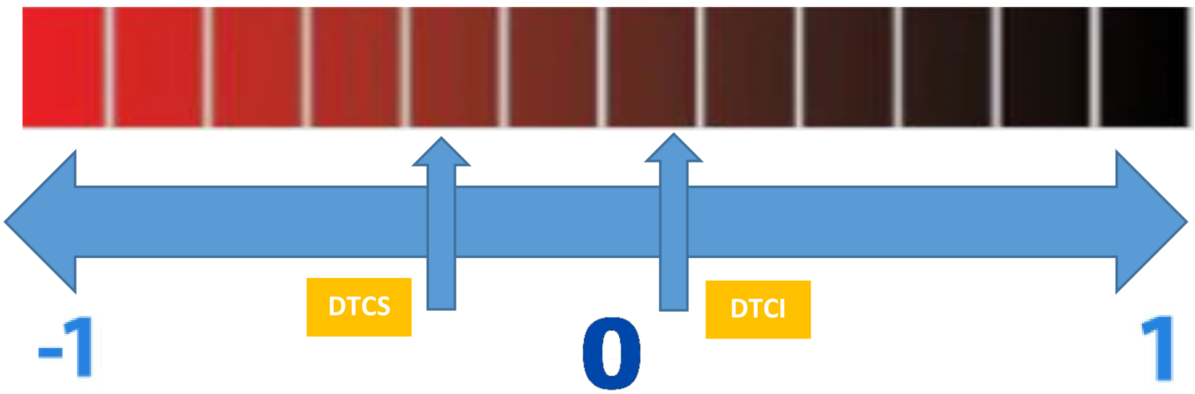
Table 9.15
DT Quantum Model. Simulated business case. Consolidated results. DTCI and DTCS coefficients

Operative_Process	Highest value	Immediate Value	Final Value	DTCI	DTCS
Manual_Loan_Analysis	100	95	30	-5,00%	-70,00%
Manual_Credit_Card_Analysis	225	220	132	-2,22%	-41,33%
Documents_Signatures	265	240	110	-9,43%	-58,49%
Physical_File_Storage	265	254	115	-4,15%	-56,60%
Physical_Files_Review	285	280	98	-1,75%	-65,61%
Manual_Payment_Applications	426	426	300	0,00%	-29,58%
Balance_Due_Certifications	205	200	98	-2,44%	-52,20%
Phone_Balance_Inquiry	135	145	165	7,41%	22,22%
Phone_LoanProcess_Status_Inquiry	115	136	295	18,26%	156,52%
Phone_CreditCardProcess_Status_Inquiry	140	140	140	0,00%	0,00%
Consolidated weighted coefficients				**0,07%**	**-19,51%**

Second approach

As a result of DTCI and DTCS coefficients, the intensity of the digital transformation process can be estimated according with the folllowing color pattern:

Image 9.24
DT Quantum Model. Color pattern for DT intensity consolidated evaluation.



Third approach

As a result of DTCI and DTCS coefficients, potential estimated savings for the organization in some key areas for future digital transformation projects, could be performed. In this case, the experience generated in these kind of initiatives could be used in order to estimate potential estimated savings in future digital transfotmation projects, as investment criteria for managerial levels. To define the potential savings, the results of the DTCS must be used, due to the fact that, at the moment of performing an evaluation about investing in a digital transformation project, experience based in organization's capacity to maintain positive effects in time due to the insertion of digital technologies must be taken into consideration for the correspondent analysis.

The estimated savings could be addressed in the following key operational areas:

1. Financial resources.
2. Workforce.
3. Physical storage.
4. Technology purchases.
5. Time.

Therefore, according with DTCS result mentioned before in image 9.15, the exposed savings could be as follows:

Table 9.16
DT Quantum Model. Simulated business case. Estimated savings in future digital transformation projects

Operational area	Estimated cost savings
Financial resources	**19.51%**
Workforce	**19.51%**
Physical storage	**19.51%**
Technology purchases	**19.51%**
Time	**19.51%**

CONCLUSIONS

It is absolutely clear that technology has been changing almost all human activities. It has taken stage as a starring role within the last ten years. Nowadays, in a wide variety of fields, we cannot consider working and living separated from technology. Moving a bit more beyond, it could be unthinkable, in a lot of human, professional and operational areas, thinking about success and growth without the participation of technology.

Why? Because technology is the visible demonstration of human´s spirit of innovation, development and growth. In addition, such evolution has appeared along with experience. Every discovery, regardless its size, complexity or impact, has contributed to human´s experience. From the age of caves to the actual peak of internet and automation, humans have been creating technology and accumulating experience. That is an endless race.
Organizations, as humans, have been exposed to such race. The mentioned evolution has involved organizations worldwide and has created a fierce market actually. It seems that there is an aggressive race to be part of the leaders in terms of innovation, technology and competitiveness. The digital transformation processes have been serving as powerful engines that have accelerated such evolution, creating a landscape in which digital processes have been crucial to guarantee success.

The way organizations put in practice and manage digital transformation issues in their processes, defines its success in market. In spite of the fact that a very important component of digital transformation in organizations is people or workforce (change-driven culture, innovation attitude, team-work), even though there is no discussion about the fact that people is the heart of change-processes like digital transformation because they are the ones that execute that new ways to do things, in the middle of such initiatives numbers and coefficients plays a crucial role to evaluate it in time.

Thus, digital transformation itself is a fantastic tool to improve organization´s competitive position in market, but it must be accompanied, besides of people´s compromise, by quantitative procedures to calculate and evaluate its impact in time. Also, seen as investments projects, digital transformation processes must have numerical indexes or coefficients to justify itself in front of decisions portfolios of managerial levels.

One of my most relevant learnings through my career, is the fact that the results of every managerial or operational decision or project must be capable to be measured in a quantitative way, in order to determine accurately its evolution in time and its impact. If a project lacks of the chance to calculate its results or evolution, there might be a problem with its design.

Therefore, *DT Quantum Model* provides a tool to calculate and evaluate digital transformation processes in oganizations, based on historic-data collection of quantity of manual tasks of determined operational processes, related with the insertion of digital technologies to automate them. There might be another techniques or methodologies to perform such analysis, but the one proposed in this book provides a simple-quantitative approach to summarise the whole process into two coefficients, in order to understand better how intense it has been and to estimate how could be the future (in terms of potential savings) if organizations would like to put in practice related projects.

If you cannot track and measure a process, then, you would not be able to control it. Based on that premise, *DT Quantum Model*, as a Diagnostic Analytics approach, would help you, my dear friend reader, to improve and strengthen your follow up and control capabilities within digital transformation processes on your organization.

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DT QUANTUM MODEL

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