Università degli Studi di Padova
Dipartimento di Scienze Statistiche
Corso di Laurea Magistrale in
Scienze Statistiche

Improvement and its organizational infrastructure: an empirical analysis of their relations through Structural Equation Modeling

Relatore: Prof. Andrea Furlan
Dipartimento di Scienze Economiche e Aziendali "Marco Fanno"

Laureando: Marcello Gurian
Matricola: 1059573

Anno Accademico 2014/2015

“*The most dangerous kind of waste is the waste we do not recognize*”
Shigeo Shingo, manufacturing expert in Toyota production plant

“*We just get something working smoothly when it’s time to improve it again*”
James P. Womack & Daniel T. Jones, *Lean Thinking*

Contents

Introduction

When, in 1990, the book "*The Machine That Changed the World*" written by James P. Womack, Daniel T. Jones and Daniel Ross was first published, it immediately caught the attention of the entire economic world. The new, revolutionary management approach that is presented in the book, born around the 50's in Japan and named *lean production*, really represented a turning point in all the manufacturing industry of that time. The lean system spread very rapidly all over the world and the knowledge about this new production system grew constantly. Basically, it represented a totally new way of managing a company, banishing all kinds of waste and focusing every activity on the pursuit of satisfying customers' needs in the best way possible. What was really striking about lean management is that, through it, Japanese companies were able to overcome the main trade-offs of the old manufacturing production system (e.g. high product quality opposed to high production time, small batches opposed to long changeovers, product diversification opposed to high unit costs, etc.), adopting a series of notions headed in the direction of process standardization, banishing waste, and involvement of people, in order to be able to provide the customers with perfect products, at the right time, in the exact quantity that was required.

The "lean universe" comprehends a huge amount of operational techniques or notions (pull system, Kanban, TQM, 5S, Just in Time, Kaizen, and many others), all consistent with the lean principles, but, at the same time, each aimed at improving a different aspect of the company. Although different each other, some of these lean techniques are similar, in the sense that they share some common aspects; for example, two different techniques can both have the purpose of aligning operational goals and strategic goals, or can be aimed at improving process efficiency, or waste elimination, or can have the effect of making people more responsible or more involved in some projects. Furthermore, it was demonstrated that the simultaneous application of these interrelated techniques often leads to higher benefits than those gained through the application of single separated activities; there is, hence, a synergetic effect when applying lean notions, that amplifies the overall benefits for the company. For all these reasons, researchers are more and more focused on the study of lean practices as *bundles* of techniques, where every bundle is made of separated and distinct techniques, but strongly correlated each other, that, therefore, can be grouped under the same construct. For what regards Improvement, analogue considerations can be drawn. As Peng et al.(2007) assess, the ability to carry on improvement initiatives is a very important form of capability, or, more precisely, of dynamic capability. According to Peng, these capabilities consist of bundles of interrelated yet distinct routines. We can see, then, how the notion of routine bundles is strictly related to Improvement and, in general, to the lean philosophy. Another significant contribution in the area of Improvement comes from Anand (2009), who assesses the importance, when adopting improvement initiatives, to comprehend an adequate organizational infrastructure.

Therefore, the aim of this work was to represent Improvement in terms of bundles of different routines; these routine bundles, then, in accordance to Anand, should represent, in the best way, the organizational infrastructure of the company. Once this task was accomplished, a model was built where Improvement is causally related to the bundles of the Improvement infrastructure; in other words, our model assumed that growing performances in one or more of these bundles automatically caused growing performances in the Improvement activities. Finally, the validity of the overall model and of the causal relations within it were tested.

Of course, these theoretical implications are based on a series of quantitative analysis. The statistical instruments that have been used are those regarding factor analysis and Structural Equation Modeling (SEM). The data on which the statistical analysis were carried out come from the third round of the *High Performance Manufacturing (HPM)* database, a wide survey on 266 manufacturing production plants located in 9 different countries (Finland, USA, Japan, Germany, Sweden, South Korea, Italy, Austria, Spain) and belonging to three different types of industry (transportation, electronics, machinery).

This work is divided into five chapters. In the first one the lean production system is presented, showing how the manufacturing world shifted from the old mass production system to the new Japanese way; in particular, lean synchronization is described in detail through its five fundamental principles: value, mapping value, flow, pull, and perfection. The second chapter is dedicated to Continuous Improvement: first what it consists of and what are the tools for improvement activities, and then its role as a dynamic capability and its organizational infrastructure summarized by its three elements (*Purpose, Process*, and *People*). The third chapter is pure statistical theory: factor analysis (both exploratory and confirmatory) and Structural Equation Modeling, that will be used in the following part. The fourth chapter is very long and represent the core of the research. After a brief description of the database and some preliminary analysis, the necessary items were extracted and divided, through factor analysis, into two parts: the first one regarding the three categories of the Improvement infrastructure (*Purpose*, *Process*, and *People*) and the second one regarding Improvement and its meta-routines (Process Management, Leadership Involvement, and Continuous Improvement). Afterwards, through confirmatory analysis, the validities of these grouping processes were tested.

In the final chapter, then, the overall SEM model is illustrated, comprehending the causal relations between *Purpose-Process-People* and Improvement. The validities of these relations are tested in the form of a system of hypothesis, as follows:

- H_1: The bundle of activities named *Purpose* has a statistically significant effect on Improvement;
- $H_{2:}$ The bundle of activities named *Process* has a statistically significant effect on Improvement;
- H_3: The bundle of activities named *People* has a statistically significant effect on Improvement.

Finally, the conclusions and the interpretations of the quantitative outcomes have been discussed in the conclusions paragraph.

Chapter 1

Lean management

1.1 Antecedents of the Lean production: craftsmanship and mass production

The philosophy known as "*lean production*" was born in Japan in the '50s, more precisely, in the Toyota production plant, thanks to the visionary ideas of a young engineer called Taiichi Ohno, who was working for the company since its foundation. Essentially, Toyota may be considered as the father of the *Lean thinking*, because up to that period nobody else had put in practise anything similar, and this is the reason why this innovative way of production is also called *Toyota Production System (TPS).*
Indeed, until 1990 nobody had ever given a name or provided a detailed explanation of what this new philosophy consisted of. It was in this year, in fact, that James P. Womack, Daniel T. Jones and Daniel Ross first published a new book that became a real milestone in this field: "*The Machine that changed the world"*. The primary purpose of this book was to give a clear explanation of the reasons underlying the trend of the auto industry of that time. In those years, in fact, data were clearly showing that North American and European automobile companies were facing a period of deep crisis, while there was an opposite situation for Japanese companies, that were steadily gaining market shares. In order to understand the phenomenon, some members of the MIT (Massachusetts Institute of Technology) set off with a very challenging program called *International Motor Vehicle Program* (IMVP). This was a sort of analytical study of the automobile industry through a very detailed analysis of a huge amount of motor companies, both in North America, Europe and Asia. The outcome of a sustained effort undertaken by researchers of MIT was that (in a few words) the auto industries of North America and Europe were relying on a production method that not only had hardly changed from Ford's mass-production system, but also had become too old to face the new challenges of that time. On the other side,

Japanese companies, with Toyota as their pioneer, were setting out advanced and much more efficient methods of production that represented a turning point not only in the auto industry, but also in the entire global economy.

Nevertheless, to fully understand the ideas of the Lean management we have to briefly go through its antecedents, going further back in time, starting from the very first car companies and their craft production methods.

At the end of the nineteenth century the car was not a common good, it was something completely unique, and there were very few companies that were able to produce automobile. One of these was the French *Panhard and Levassor* (*P&L)*. The automobile production system of companies like P&L was very different from what we are used to nowadays. Those cars were pure handicrafts. They were produced in extremely low volumes (1000 or fewer automobiles a year) and were expressively built to satisfy their customers. In fact, there wasn't enough *know-how* to allow a reasonable price for those products and car was still a product that very few fairly well-off people could afford. The low production volume and the high price resulted in the possibility of tailoring each product to the precise desires of individual buyers. The consequence was that there weren't two identical cars coming out of the factory and the standardization was totally absent. Moreover, low volumes mixed with high level of personalization resulted in the impossibility to move through the learning economies (to learn how to work better) and through the scale economies (to reduce unitary cost), thus getting expensive and little reliable products. Finally other particular aspects of this kind of production were: high decentralized organization and high skilled workforce. Each worker, in fact, was a craftsman who was able to accomplish a wide range of tasks.

The first step that the economy had to take was to move from a craft production system to a mass production system. This was possible thanks to Henry Ford, founder of the American Ford Motor Company, who, in 1908 with his Model T, completely revolutionized the way of manufacturing cars. Ford's Model T, in fact, was totally designed for manufacturing and was, as we would say today, user friendly: virtually anyone could afford, drive and repair it. Ford's most remarkable discovery wasn't the continuous assembly line, but "the complete and consistent interchangeability of parts and the simplicity of attaching them to each other" (Womack et al., 1990). Ford's idea was that if any component of the car had been totally identical and standardized, it wold have been much easier for workers to assemble them, thus saving time and money. The introduction of the assembly line occurred in 1913 when Ford realized that the continuous movement of workers from one assembly deck to the other was too time-consuming.

The interchangeability and standardization of the components allowed Ford to soar sales volume and to move very fast through economies of scale thus reducing costs. Unfortunately there was almost no degree of personalization and the customers had no opportunity to have a product specifically tailored to their needs. Briefly, Ford was able to reach incredible sales volumes and to reduce costs, but at the expense of personalization.

Such a high level of standardization goes hand in hand with the notion of the division of labour. We have immediately to emphasize that Ford brought this concept to its ultimate extreme. Every worker in Ford’s factory “was responsible for just one single task, such as to put two nuts on two bolts or perhaps to attach one wheel to each car. […] The fact that he might not even speak the same language as his fellow assemblers or the foreman was irrelevant” (Womack et al, 1990). The task cycle of the average Ford assembler was just 2.3 minutes. The main consequence of this extreme division of labour was that (just like the car components) every worker was completely interchangeable: the task they were asked to accomplish were so narrow and simple that every other worker was able to perform. Each worker, then, was perfectly replaceable.

Coming back to the product, it’s necessary to remark a very important aspect: the easiness of use. Although it was made of many components Model T was actually a very simple product. It was easy not only to drive but also to be fixed up. In case of any problems, in fact, the car was equipped with a manual, written in question-and-answer form, explaining how owners could use very simple tools to solve any of the problems that were likely to crop up with the car. And it didn’t matter if the owner was a farmer with a modest tool kit available, he was always able to solve the problem on his own.

Of course, Ford’s mass production system was not free of disadvantages. The strong standardization and the necessity to reach economies of scale made the product differentiation impossible, thus giving the customers no opportunity to choice among a range of products or to customize the existing ones. Moreover, the extreme division of labour created malcontents among the workforce, who was forced into accomplishing the same task all day long. The mass production required also a very centralized organization, where everything had to be made in the same place. Finally, Ford’s shop floor was full with high-specialized equipment to fully exploit benefits of big volumes. These machineries were able to keep high work pace but implied high set-up costs.

A step forward in the mass production system was taken when Alfred Sloan became president of General Motors. He somehow made the system Ford had pioneered complete. Firstly, Sloan reorganized GM creating decentralized divisions and profit centres, that were asked to provide reports based on numbers describing the situation of each division; hence he decentralized decisions to manage more efficiently the organization. He also developed stable sources of outside funding linking the company with banks and credit firms. (Ford, on the other side, had never relied on loans by banks, but has always been financially independent). Finally, Sloan was also able to widen the range of products offered by GM, without losing the advantages of the economies of scale. His plan was to standardize some mechanical items and alter the external appearance of each car, introducing a series of "hang-on features" (automatic transmissions, air conditioning, radios, …) which could be installed in existing body designs.

Although Sloan's ideas represented a sort of innovation from many points of view, it didn't take the distance from the concept of mass production, and its limits were still evident also in Sloan's GM. Anyhow, everything was enough good for that time and Ford's mass production methods brought a lot of success. In the half of the twentieth century US car companies dominated the world automotive industry and the US market accounted for the largest percentage of the world's auto sales. In 1955 the three main American enterprises: Ford, General Motors and Chrysler, gained 95 percent of world sales, and six models accounted for 80 percent of all cars sold.

By 1973 something changed, as the petrol crisis put in troubles the entire automotive industry. It was in this period that in Japan we could see something new coming to life, something that represented a real leap in the field of manufacturing.

1.2 The Lean leap

Since its foundation in 1937, by Kiichiro Toyoda, up to the middle of the twentieth century, Toyota was a relatively small Japanese motor company with a level of production remarkably lower than its American competitors like Ford or GM. Nevertheless in 1950 Eiji Toyoda and his production engineer Taiichi Ohno started thinking and developing a new production philosophy that brought a striking success to the company.

First of all, Toyoda and Ohno realized that the typical mass production system that Ford had applied in his firms was not congruous for the Japanese market. The market was smaller and more inclined to offer more product variety rather than big volumes. The economy was weak, suffering the consequences of the World War II and the workforce was unwilling to be treated as an interchangeable component, good to accomplish one small single task for numerous times a day. At the same time the previous crafts production system was inadequate too: it required high costs, high skills and it was not suitable for the introduction of innovative technologies. Another path needed to be found. And they did manage: that's how the lean production was invented.

The core idea of the *lean production* can be summarized as "*banish waste*", and for waste we mean every possible activity that is not adding any value to the product or service. Value, as we will more clearly understand, is defined by the customer, that can be either internal or external. Every activity that is not adding any value for the customer has to be eliminated, since it represents waste. Furthermore, the output of any operation has to be created and delivered when it's required, in the exact amount required, and with no defects *(just in time).* The consequence is that in a production plant every component is produced just if the following operation downstream requires it. This is the "revolution" embodied in the *lean thinking,* and it carries a series of both theoretical and practical consequences that will be discussed later on. The main and probably most immediate consequence of this revolution is the elimination of a huge part of the inventory (raw materials, work in progress and finished products). Taiichi Ohno believed that the tendency to accumulate stocks was an outdated state of mind, no more suitable for the economy of that time and that had to be overcome.

Generally speaking, the lean thinking is strictly related to the elimination of waste (or *muda*, in Japanese); but unnecessary stocks is just one of the possible *muda* in a production process. Ohno identifies 7 types of waste (Ohno, 1988):

- *Over-production*: level of production superior to what is required by the customer;

- *Waiting time*: time when no modifications are applied to the product; for example when workers are waiting for necessary materials to be available;
- *Transport*: unnecessary movements of components within the assembly plants of the factory;
- *Process*: production processes not adequately designed and therefore producing products that do not match customer's desires;
- *Inventory*: goods in stock (in the form of work in progress (WIP) or finished goods) that represent a capital investment that still hasn't realized its return;
- *Motion:* time when workers or machinery are moving; it does not add any value and could be used for other activities;
- *Defective goods*: not adequate product quality.

In addition to these *muda* Taiichi Ohno identifies other two types of waste:

- *Muri (Excessive loading):*overload of workforce or machinery utilization; it can cause injuries and illnesses for the first and wear and breakdown for the latter;
- *Mura (Excessive variability):* alternation of moments of high and low workload due to the not-standardized demand.

Focusing on waste elimination and trying to optimize those activities that add value to the customer, Toyota simultaneously managed to: reduce costs significantly, raise the quality level and improve efficiency.

Ohno believed also that mass production system was not centred enough on product defects, since the main concern was just to let the line flow instead of solve problems. In case of any problems or defects that occurred with the product in a typical mass production plant, in fact, nothing was done until the product reached the final stage. It was just in that moment when some inspectors checked the entire product up, only then if they discovered some defects those were solved. This problem-solving approach of passing on errors to keep the line running caused errors to multiply endlessly and was massively more expensive and time-consuming compared to Toyota's approach of solving problems immediately when they are detected. Indeed, once a defective part had become embedded in a complex vehicle, an enormous amount of rectification work was needed to fix it. And because the problem would not be discovered until the very end of the line, a large number of similarly defective vehicles would have been built before the problem was found. On the other hand, of course, solving problems at the source implies stopping the line. For this reason, Ohno decided to give every worker the right and the means to stop the line whenever a problem emerged by placing a cord above every work station. When it happened, an entire team of worker came to the assembly station where the problem had been identified and started thinking of how to solve it. The workers were also taught not to treat problems as random events, but to always trace them back to their ultimate cause, thus finding a solution that prevented errors to occur again. This was possible through a system called "*the five why's*": by asking why five times it was possible to get back to the real starting cause of the problem, that was, very often, an organizational issue. Initially, these experiments were stopping the production line, rendering the workers discouraged. Nonetheless, as the work team gained experience identifying and tracing problems back to their ultimate cause, the number of errors dropped dramatically; and little by little it reached a situation where in Toyota assembly plant the line never stopped, although every worker had a possibility to do it.

Afterwards, Toyota implemented a new approach to the system of suppliers, in order to enhance cooperation between the firm and its suppliers to simultaneously reduce costs and improve quality. Suppliers were divided in different tiers, where first-tier suppliers were in strict relation with the company (almost part of it), and used to take part of activities involving e.g. the design of new products.

The design process itself underwent significant changes. It was carried out by a team, headed by a team leader, and through a constant interaction of people and knowledge new ideas took shape faster and more frequently.

Even though long and full of obstacles, the process of transformation from a mass production to a Lean production system brought amazing results. In Figure 1.1 we can notice some emblematic data showing the width of the gap that occurred at the beginning of '80s between US and Japanese car companies.

	USA	Japanese
Productivity (hours/vehicle)	31	16
Defects per 100 cars	130	45
Space for assembling	0,75	0,45
Inventories of parts	2 weeks	2 hours
Average hours for design (millions)	3,1	1,7
Average time for development (months)	60,4	46,2
Supplier contribution to design and development	14%	51%
Number of suppliers per factory	509	170
Proportion of components from one source	69,3%	12,1%

Figure 1.1: Productivity gap between USA and Japan at the beginning of '80s
(Source: Womack, Jones and Roos, *The Machine that changed the world*)

The most significant conclusion to be drawn from this data is that Toyota was able to overcome the trade-off between productivity and quality, showing that a high level of productivity (that means low costs) did not necessarily affects quality, and vice versa; a very efficient definition of Lean synchronization provided by Slack et al. (2010) clearly explain this aspect: "The key principle of *lean operations* is relatively straightforward to understand: it means moving towards the elimination of all stocks (*muda*) in order to develop an operation that is faster and more dependable, produces higher quality products and services and, above all, operates at low cost".

1.3 The five Lean principles

Once identified the guidelines of the rise of Lean production, we go through its basic ideas and principles. A theorization of this new approach has been provided by James P. Womack e Daniel T. Jones in their book "*Lean Thinking*". In this book the authors express their opinion that Lean management represents the evolution of the Toyota Production System and it is based on the notion of "*lean thinking*", that promotes "a way to do more and more with less and less – less human effort, less equipment, less time, and less space – while coming closer and closer to providing customers with exactly what they want" (Womack and Jones, 2003).

An operation can be defined lean when, within it, all materials move in a continuous flow passing through processes that constantly add value.

Lean philosophy embraces three main concepts:

- Eliminate waste: every *muda* must be banished, that is every activity that, although resources-absorber, does not add any value to the product represents waste and therefore has to be eliminated;
- Involve everyone: the system has to encourage every worker to a strong sense of responsibility and commitment. It requires team groups for problem-solving, job enrichment, job rotation, job enlargement, in order to convey a sense of ownership in the work place. Everyone has to be aware of his/her important role in the reach of organization's goals;
- Continuous improvement: the notion that big-scale improvements in the organization come from small step-by-step improvements conducted in the form of a rigorous cycle activity where new ideas constantly question the previous way of doing things.

Lean synchronization, then, consists of five main and very important principles (Womak and Jones, 2003), that are listed below and that will be faced afterwards one by one in detail:

1. Specify value
2. Mapping the value stream
3. Flow
4. Pull
5. Perfection

1.3.1 Specify Value

The starting point for lean thinking is the notion of *value*. Value can only be defined by the ultimate customer. And it's only meaningful when expressed in terms of a specific product (a good or service, and often both at once) which meets the customer's needs at a specific price at a specific time.

Value is created by the producer. From the customer's standpoint, this is why producers exist. Nevertheless, it is not easy for the producer to come to a clear definition of value, mainly because it is often skewed everywhere by pre-existing organizations, technologies, and undepreciated assets, along with outdated thinking about economies of scale. Many managers around the world tend to say, "This product is what we know how to produce using assets we've already bought, so if customers don't respond we'll just adjust the price or add bells and whistles". So, defining value is not so straightforward, as producers mainly tend to keep on doing what they already do. On the other hand, many customers are not able to express they are clearly interested in, it occurs frequently that they just ask for variants of something already existing. When producers or customers decide to rethink about value they often get into simplistic formulas like "less cost", "more product variety", "additional services", "faster deliveries". What they should be doing, instead, is fundamentally rethink value from the perspective of the customer. They should ask themselves: what do the customers want? Which product features are really important? It's very common, in fact, to fall into problems of *over-design*, that is a product too sophisticated for the customer needs, as well as *under-design*, that is a too simple product. Both these two kind of mismatch between demand and offer represent *muda*, and should be avoided. Companies that do really care about value definition set out all the possible tools to avoid incongruences between producers and customers; one of these tools is, for example, the *Quality Function Deployment* (QFD) or *House of quality*, which is a purely efficient instrument that allows the final structure of the product to be effectively aligned to customers' needs.

Another reason why defining value is such a tough nut to crack, lays in the fact that it is often the result of activities accomplished by different companies, every of which tends to define value in a different way, thus focusing mostly on self-interest rather than looking through the customer's eyes.

The search for value necessarily starts by challenging the traditional definition of value, it needs to be redefined in the light of the relations between the company and the customers, as well as its suppliers (*kaiaku*). Afterward, the actual concept of value has to be constantly put in discussion, questioning if it is still the best definition possible (*kaizen*)[1].
Having specified the value of a product, the next step is to identify a *target cost*, based on the amount of resources that were utilized. Traditional companies fix the selling price basing on a margin of profit and then working backward to find out what is the price that ensures that profit. Lean companies, in contrast, fix the price by asking "What the product cost is, once eliminated all the unnecessary activities and made the production line flow?". In this way, this kind of companies can bear a much lower target cost than the others.

1.3.2 Mapping the value stream

The *value stream* is the set of all the specific actions required to bring a specific product (whether a good, a service, or a combination of the two) to the final customer through three critical management tasks of any business: the *problem-solving task* (from concept to product launch), the *information management task* (from order taking to delivery) and the *physical transformation* task (from raw materials to finished product).
The next step in lean thinking, is to identify the entire value stream for each product (or product family), in order to detect and eliminate possible *muda*.
Specifically, this analysis will almost always show three types of activities along the value stream:

- Activities that intrinsically create value;
- Activities that do not create value, but are unavoidable with current technologies and production assets (Type One *muda*);
- Activities that don't create value and are avoidable (Type Two *muda*).

[1] *Kaiaku* means a radical change (breakthrough) to eliminate *muda*
Kaizen means a gradual and continuous improvement of an activity to eliminate *muda*

Companies must identify the value stream in order to eliminate first the type two *muda,* and subsequently develop new techniques to eliminate (or reduce as much as possible) type one *muda,* thus channelling efforts to the first type of activities.
Through the value stream mapping, it is possible to map the entire flow of both materials and information, to appropriately discriminate between value-adding and non-value-adding activities, as well as to identify where future improvement activities should be focused (*kaizen*).
Moreover, the value stream mapping has to be leaded *in loco*, where the production processes takes place, usually with a real "walk" around the production plant (*Gemba walk*).

1.3.3 Flow

Once value is precisely specified, the value stream for a specific product is fully mapped, and obviously wasteful steps eliminated, here comes the time for the next step in lean thinking: make the remaining, value-creating steps flow. This step, however, requires a complete mental rearrangement.
It seems a common-sense conviction that activities ought to be grouped by types (functions, department, …) so they can be performed more efficiently and managed more easily. In addition, it seems like further common-sense that these activities have to be performed in batches. This batch-and-queue production mode implies high resources utilization rate, therefore it seems an efficient way of doing things.
Actually, the truth is that batches always mean long waits, as the product patiently waits for the department's changeover to the type of activity the product needs next. Tasks can almost always be accomplished much more efficiently and accurately if the focus is represented by the product itself and is worked on continuous flow from raw materials to finished goods; this new approach gives several benefits, among which the drastic reduction of inventories and the drop of throughput time[2] both in production processes and in design and delivery processes.

[2] *Throughput time*: the total period a component requires to pass through the entire process

To create a continuous flow it is essential, as already mentioned, to focus on the product itself. What is more, the company also needs to break the old schemes of departments and functions that represent an obstacle to the flow creation, and to generally rethink all the processes in a way that avoids backwards, line stops and scraps.

The introduction of flow is possible only when the cycle time[3] coincides with the *takt time,* that is the available production time divided for the demand rate. The *takt time* sets the pace the production must have to meet customer's demand. In the lean organization the *takt time* is clearly declared, so that every worker is acknowledged for the necessary work rhythm. Workers should have a clear idea of the work pace and if the production is aligned to the *takt time,* and they can do this fast, with a glance. Therefore, lean thinking comprehends a series of visual control boards, called *andon*, all along the line to satisfy this necessity as well as to be aware of possible errors or line stopping.

Another essential notion in a lean company that aims at creating flow is *Just in Time* (JIT). JIT depicts the philosophy of delivering a product to a customer exactly in the time it is demanded by aforementioned, additionally, what is vital, the product must be perfectly prepared and available, representing impeccable quality with no waste, right away in the moment one asks for it. *Just in Time* works efficiently only when the set-up times of machines are drastically reduced. To do so Lean thinking promotes the use of several small machines rather than one large one, since they allow simultaneous processing, thus being more robust, flexible, and easier to move and manage. Moreover, the use of *SMED* techniques (*Single Minute Exchange of Dies*) to reduce set-up times is highly recommended.

Even if machines allow fast set-up times, JIT is not efficient if the workload is not adequately levelled. *Heijunka*, in fact, means this: smooth the workload to reduce the unevenness. Making the same amount of different products each interval has multiple benefits over producing one type of product as long as possible to reduce changeovers. Apart from reducing the risk of unsold products and being more flexible producing at customer demand, that means sequencing the orders according to a repetitive pattern (*single-piece flow*)[4], levelling out the workload creates a balanced use of labour and machines, and a smooth demand of upstream processes and suppliers.

[3] *Cycle time*: the time between the conclusion of an output and the conclusion of the following one

[4] *Single-piece flow:* a state where operations work on one product at a time, instead of working on batches

In this system machines must be 100% reliable, otherwise all the efforts to reduce variability and reach standardized processes would be vanished. To prevent machines to stop working and to make them totally reliable, a set of techniques called *Total Productive Maintenance* (TPM) has to be put in practice. They are all based on the idea that operators have to be the responsible of the correct work of machines. Their duty is to take care of maintenance, lubricating, cleaning, adjusting problems, collecting data. Operators are asked to do so as they know the best machines they work with. As regards conditions monitoring, operator's tasks are made easier in the situation when some fail-saving techniques are adopted, so-called *Poka joke.* Thanks to *Poka-Joke* it is possible to prevent a single wrong component from going on to the next stage, by making mistakes absolutely visible and forcing operators (even the distract ones) to solve the problem.
A strictly connected notion in this topic is what is called *Jidoka* (Automation human touch); it implies a transfer from human intelligence to machines, allowing machineries to detect defective components and automatically stop waiting for the operator to come and fix it.
All this new elements in the production processes need an adequate working environment. The *5S system* (Sort, Straighten, Shine, Standardize and Sustain) can be seen as a continuous process of improving the working environment, thus making workers operate in the best conditions:

- *Sort (Seiri*): Eliminate what is not needed and keep what is needed;
- *Straighten (Seiton*): Position things in such a way that they can be easily reached whenever they are needed;
- *Shine (Seiso*): Keep things clean and tidy; no refuse or dirt in the work area;
- *Standardize (Seiketsu*): Maintain cleanliness and order, perpetual neatness;
- *Sustain (Shitsuke*): Develop a commitment and pride in keeping to standards.

1.3.4 Pull

The *pull* system is a core revolutionary notion in lean management. It allows an organization to design, produce and deliver what a customer demands in the exact moment when he/she asks for it. To do so it is necessary to let the customer *pull* the product from the company, rather than pushing it onto the customer (*push* strategy). The *pull* doctrine could be summarized simply as “don’t make anything until it’s needed, then make it very quickly”.

The best way to understand the logic of pull thinking is to focus on a customer expressing demand for a product, and to work backwards through all the steps required to bring the desired product to the customer. The production process on a certain stage has to be activated only if the following stage downstream requires it.

One of the most important tools for achieving the *pull* strategy is the *Kanban* system. The *Kanban* is properly an instruction card that works as a signal to start production (or purchasing) of a component only when required by the demand. *Kanban* is sent from one production stage to the upstream stage to signal that components are needed. It achieves *pull* in the sense that, when a *Kanban* is sent, it tells the upstream process to make parts, so it activates production only when it is needed.

There are three types of Kanban: move Kanban, production Kanban and sale Kanban. The move Kanban indicate which component has to be moved, in which quantity and where it has to be moved; the production Kanban signals which and how many components has to be produced; the sale Kanban is similar to the move Kanban but it’s generally used for external customers.

1.3.5 Perfection

Once an organization fully embraces the four principles we have talked above, the improvement in all kind of processes never stops. Indeed, the four principles interact each other in a virtuous circle that makes the identification of *muda* easier, thus paving the way for potential further improvements. Indeed, getting *value* to *flow* faster always exposes hidden *muda* in the value stream; and the harder you *pull,* the more the impediments to flow are revealed and can be removed.

What emerges from this virtuous interaction of the lean principles is that total perfection can never be reached. It looks to be impossible, but the effort to try provides inspiration and direction essential to make progress. This endless pursue for better ways of doing things is fundamental for the entire lean thinking; it is believed, in fact, that in absence of this stress for perfection, improvement is temporary, more than stable and continuous, since the tendency to do in the old (and wrong) way would prevail.

It is essential in a lean organization that this state of mind inclined to perfection through continuous and ceaseless improvement is shared by all the people within, not just by the top management that takes the most important decisions. The concept of *involvement of everyone* is very strong in the lean thinking, and is emblematic to describe the lean approach to people management. An approach strongly based on the respect for humans, through politics that encourage equality, autonomy, discipline, quality of the working life and responsibility. Workers are taught to exploit their personal capabilities and skills for the organization's sake. A famous Toyota slogan says: "Build people before building cars". (Licker, 2004).

Chapter 2

Continuous Improvement

2.1 The elements of Continuous Improvement

Before starting talking about what Continuous Improvement is, we'd better go one step back and talk about improvement. Improvement is properly an activity aimed at filling the gap between real performance and desired performance within operations or processes (Slack N. et al., 2007). It means closing the gap between what "we are doing" and what "we want to do". Actually, improvement is not that simple to be carried out, and even well-implemented improvement strategies can lose their burst after some time. To make it work efficiently you need a detailed strategy of the improvement activity (defining roles, responsibilities, resources, …), as well as an environment that creates the conditions for everyone to contribute to improve (not only a top-down strategy) and a state of mind that considers improvement not as an intermittent exercise, but as a continuous evolutionary cycle.

However, the fundamental driver for every improvement activity is, as it was clarified above, the gap between the actual performance and that required for meeting the organization's goals. To face this challenge in the right way the starting point consists of three tasks: analyse the current performance, define a series of target performance goals, and systematically compare the current performances to the target ones.

To analyse the current performances it's fundamental to have a clear idea of what *Key performance indicators* (KPI) take into account, whether detailed measures or more aggregated ones (in this field the *Balanced Scorecard* can turn out to be a very useful tool). To set the performance goal, an organization can choose different kinds of targets: on historical base, strategic targets, external targets (*benchmarking*). Finally, there are also tools used to correctly compare current and target performance, like the *importance-performance matrix.*

Once determined how to analyse performances, there are two possible ways to put in practise the improvement, and this two ways reflect two different improvement philosophies: radical improvement (*Kaiaku*, or *breakthrough*) and continuous improvement (*kaizen*).

Radical improvement consists of improvement based on innovations; it asserts that the main driver of improvement is a radical change in the way of doing things, that brings massive performance improvement. These changes happen to be really expensive for an organization and their purpose in to unsettle the previous operational structure. Examples of *breakthrough* constitute: the introduction of a new ERP (Enterprise Resource Planning) to completely reconfigure production, or BPR (*Business Process Reengineering*) that can be defined as “the fundamental rethinking and re-design of processes to obtain substantial improvements in KPI like cost and quality” (Hammer and Champy, 1993).

The other improvement philosophy is much more interesting to us, given the purpose of this work. Continuous improvement adopts an approach based on a series of small but endless incremental performance improvements of existing products/processes, that become permanent part of an organization’s processes. The collection of this steady “small wins” plays a fundamental role in the global performance of the organization. The performance goals are seen as a moving target and are the main driver that stimulates the creation of these small ceaseless improvements. What is really important in the continuous improvement philosophy is not the improvement activities rate, but the burst towards them. In this sense, continuous improvement can be defined as “an ongoing activity aimed at raising the level of organization-wide performance through focused incremental changes in processes” (Bessant and Caffyn, 1997; Wu and Chen, 2006).

Continuous improvement is not revolutionary, and its aim is to transfer its mentality into the organization’s culture. Therefore, it involves everyone in the company, from managers to workers, from suppliers to customers. It focuses on the experience gained on the workplace and stresses the attention on adaptability and team work.

As the reader might have already understood, continuous improvement goes hand in hand with lean thinking. Indeed, if we looked for some origins of this improvement philosophy, we would probably find out that Taichii Ohno and his *Toyota Production System* (TPS) have very much to share with it. All the notions discussed in the paragraph dedicated to the lean principles are strictly related to continuous improvement. The *pull* and JIT principles (to make just what customers want when they ask for it), *Jidoka* (to level out production), *one-piece flow, Poka-Yoke* (mistake-proof processes) are all techniques adopted to continually improve existing products and processes, hence can be categorized under the CI scheme. The idea that efforts to adopt lean techniques result in an endless pursue for perfection seems to coincide with the continuous improvement definition as a collection of small ceaseless steps to expose waste and eliminate it.

2.2 The continuous improvement techniques

The lean thinking promotes the use of continuous improvement (*kaizen*) to deliver better products and processes and fully meet customer needs. To do so, an approach based on quality is undertaken, since quality can only be reached (and actually this is its definition) when there is full correspondence between the product/service specifications and the customer expectations. Therefore, a prerequisite for CI is that all the organization understands the importance of quality and the way it can be improved to completely satisfy customer needs.

Many different approaches to quality have been studied, always arising considerable interest. Among these, the most important is probably the *Total Quality Management* (TQM), developed between the 70's and 80's. TQM is an approach aimed at guiding the organization towards improvement through the search for total, global quality. This means that quality is the real bulk of operations and the organization must no longer think about how to avoid defective products to reach the customers, but how to avoid the creation of defective products. Every process has to be improved focusing on quality, trying to reach the so-called *error-free* production. There is, then, a shift from a reactive approach towards quality (correct errors when detected) to a more proactive approach (prevent errors form happening). TQM also stresses the attention on the contribution of everyone in the search for total quality. Not only those people who are directly involved in the production processes, but everyone in the entire organization must have clear awareness of their role in achieving high quality, and everyone must actively contribute to it.

Working for total quality means also monitoring and reacting when performance indicators are too distant from the levels considered acceptable. In this sense, TQM promotes the use of *Statistical Process Control* (SPC). SPC consists of analysing a sample or a group of samples of a product or a process indicator for a certain time range, to asses if the process is under control or not. To do so, a set of statistical tools are usually used (histograms, correlation matrices, …), but the most important one is the *control charts.* The *control charts* are graphs monitoring the trend of a certain aspect of production over time to determine if that process is in a state of statistical control, or in the opposite case, if it needs some corrective actions (Slack et al., 2007). The control charts' purpose it not only to monitor processes, but also to improve them reducing their variability. Variability, in fact, is something undesirable, since it hides the trend and makes difficult to understand the process performance. SPC is able to reduce variability by discriminating between variations coming from sources common to the process and variation coming from special sources. Eliminating the latter, it's possible to reduce the process variability. Finally, we have to add that SPC is not just a way to monitor and control processes. Statistical control, in fact, allows a greater knowledge of products and processes that can be an important source of competitive advantage.

Although very efficient, a continuous improvement activity can turn to be unsuccessful if it's not adequately standardized. In order to make a CI activity organization-wide and over time, in fact, it should be defined with a scientific method, through a standard set of steps. In particular, the burst through improvement never stops only if the CI is represented by an endless cycle of constant rethinking of current processes.

There are two mainly used models:

a) PDCA cycle: it is also known as *Deming cycle*, from D. Edwards Deming, who is considered by many to be the father of modern quality control. It is an iterative four-step used for the control and continuous improvement of products and processes. The four steps of the cycle, that we can see in Figure 2.1 (a), are the following:

- *Plan (P):* it consists of an analysis of the situation, collecting and analysing data, to define an action plan aimed at improving the actual performance;

- *Do (D)*: it means implementing the action plan; in this phase other *PDCA* micro-cycle might be needed to solve possible implementation problems;
- *Check (C)*: it means study the outcomes and compare them to the expected results to find out if the new solutions that were implemented has brought significant improvements;
- *Act (A):* After the *Check* step, if the plan has proved successful it can be consolidated and standardized, otherwise a new *PDCA* cycle starts, aimed at determining the root causes that lead to the failure.

b) *DMAIC cycle:* it is a data-driven improvement cycle used for improving and stabilizing processes. Unlike the *PDCA* cycle, the *DMAIC* cycle is made of five steps. It is often used in *Six-Sigma* projects (we will discuss *Six-Sigma* later), although it's not exclusive of this approach, and it embodies a stronger scientific approach. The five steps, that we can see in Figure 2.1 (b) are the following:

- *Define (D):* in this step the problem is clearly articulated and it's usually fixed a formal improvement target;
- *Measure (M):* it is the validation of the problem through data collection (to see if it's actually worth resolving). There is decided what should be measured and how it should be measured it, because real improvement will be evaluated comparing these measures at the beginning and at the end of the improvement process;
- *Analyse (A):* the purpose of this step is to identify, validate and select root causes of the problem, through an analysis of a number of potential root causes;
- *Improve (I):* The purpose of this step is to identify, test and implement a solution to the problem. A number of possible solutions are tested and those successful are implemented;
- *Control (C):* Finally improvement has to be monitored to ensure continued and sustainable success. Then, the cycle restarts defining problems that avoid further improvement.

In both *PDCA* and *DMAIC* cycles the last step ends with “the cycle restarts”. Indeed, a correct improvement philosophy can be implemented only accepting the idea that improvement cycles never stops, since improvement is integral part of the organization.

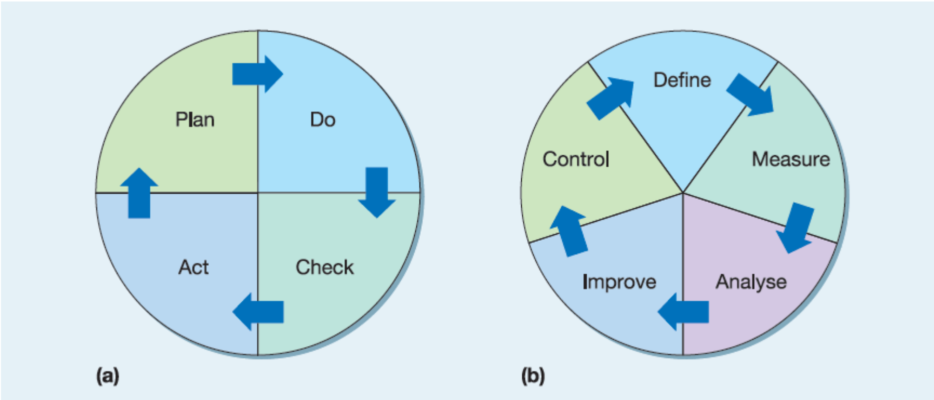


Figure 2.1: The *PDCA* cycle (a) and the *DMAIC* cycle (b)
(Source: Slack et al., *Operations Management*, 2007)

Talking about the *DMAIC* cycle mentioned the *Six Sigma* approach. Going briefly into it, it is noticed what does it consist of. *Six Sigma* is a set of techniques and tools for process improvement that mixes elements of both radical and continuous improvement and it is strictly related to *Statistical Process Control (SPC*). It was developed by Motorola in 1986, Jack Welch made it central to his business strategy at General Electric in 1995. Today it is used in many industrial sectors. *Six Sigma* seeks to improve the quality of process outputs by identifying and removing the causes of defects and minimizing variability in manufacturing and business processes. When in 1980 Motorola was trying to improve its quality levels through elimination of defects, it was realized that there were some processes that produced defects in any case, since they were embodied in the real design of the process. The only way to eliminate those latent defects was to make process specifications extremely detailed, reducing tolerances as much as possible. Hence, the password became “standardization”, and variability became synonymous of “bad”. The term "*Six Sigma*" comes from the notion that if one has six standard deviations (σ) between the process mean and the nearest specification limit, practically no items will fail to meet specifications. The *Six Sigma* philosophy assesses that improvement activities can be successful only if they are supported by adequate resources and staff training. Hence, it promotes a special infrastructure of people within the organization ("*Champions*", "*Black Belts*", "*Green Belts*", "*Yellow Belts*", etc.) who are experts in these improvement methods.

2.3 Continuous improvement as a *dynamic capability*

Continuous improvement initiatives have massively proliferated among manufacturing organizations worldwide. Organizations nowadays seem to compete no longer on processes, but on the ability to continually improve processes (Teece, 2007). Nevertheless, not all the CI initiatives that have been deployed have been successful. Results of a 2007 survey of US manufacturers depicted that among those plants that had deployed lean manufacturing techniques, only 11% of them considered their CI initiatives to be successful (Mendelbaum, 2006).

In order to understand what key elements of a continuous improvement activity led to success, we have to start from the very essence of CI, that is its role as a capability and, in turn, as a bundle of interrelated routines.

Continuous improvement represents a key capability in every organization. When we talk about "capability" we intend the strength or proficiency for performing specific tasks. Following the *Resource Based View* of the firm (RBW)[5], resources and capabilities are the constituents of sustained competitive advantage for the company. But what are these capabilities made of? Peng et al. (2007) asses that capabilities, including continuous improvement and innovation, consists of a bundle of interrelated yet distinct routines, which are significantly related to operational performances. We can define routines as "regular and predictable patterns of behaviours" (Grant, 1991); through routines, certain clusters of resources are utilized to achieve desired outcomes. Nevertheless, capabilities do not reside in routines taken individually; they emerge from the synergistic interplay among multiple interrelated routines that are complementary and they reinforce each other. This approach is absolutely revolutionary: speaking about routines as the foundation of

[5] *The Resource-Based View (RBV)* of the firm is a model that assesses that the basis for the competitive advantage of a firm lies primarily in the application of a bundle of valuable tangible or intangible resources at the firm's disposal

capabilities, Peng et al. (2007) show a completely new perspective of looking at operation capabilities. The innovative element of this perspective lies in the fact that capabilities are mostly inimitable. Since routines are the repetition of regular patterns, their force comes from the experience; through experience people within the organization can develop a range of tacit skills that enables experience and are the source of capabilities. Moreover, when these routines are difficult to observe and are the result of synergies between other routines, the inimitability-effect is amplified and becomes more and more difficult for competitors to observe them. In other words, “the difficulty of observing the complex interplay between the multiple interrelated routines in a capability, coupled with the path dependent and tacit nature of each individual routines creates significant barriers to imitation or substitution of comparable capabilities (Peng et al., 2007).

In particular, talking about continuous improvement capabilities and its underlying routines, we can identify three groups of routines:

- *Continuous improvement*: it refers to sustained incremental improvements of existing products/processes. It includes activities aimed at modifying and refining existing products, equipment, process technologies and operational practices;
- *Process management*: it involves efforts to map and improve organizational processes through cost reduction and more efficiency;
- *Leadership involvement*: it aims at stimulating improvement capabilities through leadership involvement at all levels of the organization. Leadership is seen as the driving force of quality improvement efforts and managers should motivate employees’ participation in continuous improvement.

As we’ve just explained, the continuous improvement capability is the ability to consistently improve current processes and learn new ones to increase efficiency. It is, hence, a continuous and dynamic activity that systematically produces new ways of doing things, it is not a one-time change. In this sense CI fits into the notion of “*dynamic capability”,* where, by “*dynamic capability*” we mean “a learned and stable pattern of collective activity through which the organization systematically generates and modifies its operating routines in pursuit of improved effectiveness”(Zollo and Winter, 2002).

However, for dynamic capabilities to generate competitive advantage, it is critical that they include a comprehensive organizational context, a coherent infrastructure, in order to coordinate and execute improvement projects (Figure 2.2). It is proved, in fact, that CI deployments that lack adequate coordination lose traction and become ineffective after realizing initial gains (Choo et al., 2007).

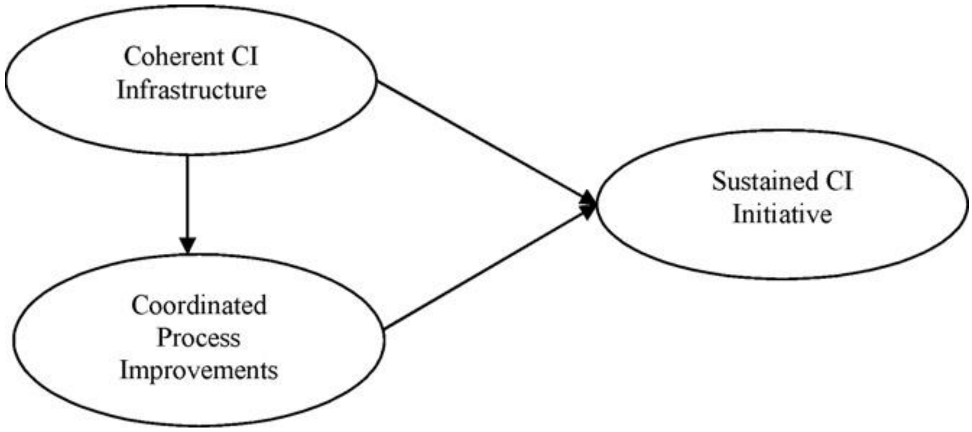


Figure 2.2: Relationship between CI initiatives and CI infrastructure
(Source: *Journal of Operations Management*, 27 (2009) 444–461)

2.4 Continuous improvement infrastructures

Traditional management methods typically involved top-down strategic planning, where the responsibility for the formulation and implementation of organizational strategies belonged exclusively to the top management. Such method was inadequate for the development of *dynamic capabilities*, firstly because of its slowness (there are several layers from top-management to front-line employers) and second because it inhibits bottom-up learning.
In order to facilitate the dynamic creation of front-line capabilities that provide successful and coherent response to environmental changes, the Bartlett and Ghoshal's scheme of organizational infrastructure seems to be more suitable. According to this scheme the organizational framework is in the form of "*purpose-process-people*". *People* are treated as knowledge resources that cooperate in the discovery of better ways to execute *processes*, thus accomplishing broader organizational *purposes* (Figure 2.3). By allowing and even

facilitating proactive changes at the middle and front-line levels while maintaining strategic congruence, such management approach provides an effective framework for organizational learning and the development of *dynamic capabilities*. (Teece et al., 1997).
Below the analysis, one by one, of the three categories that this framework is made of.

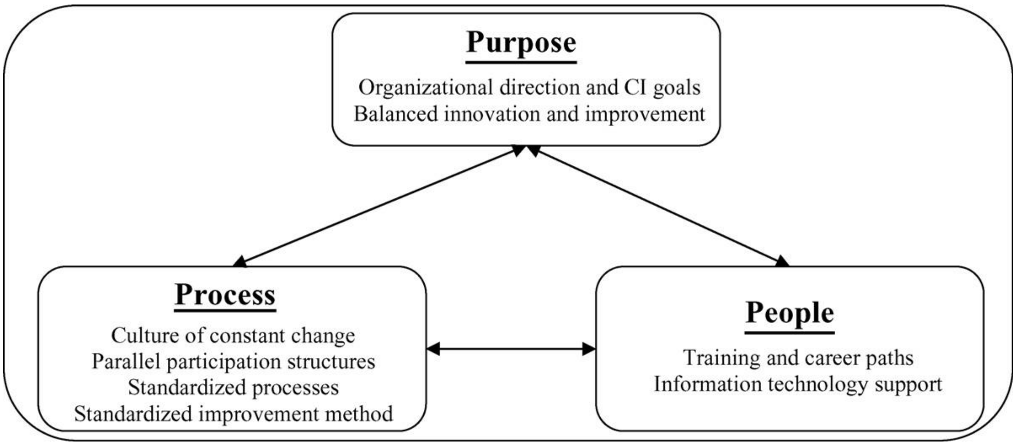


Figure 2.3: The purpose-process-people CI infrastructure
(Source: *Journal of Operations Management*, 27 (2009) 444–461)

2.4.1 Purpose

The purpose category covers the formulation and communication of organizational and project goals for CI. In particular, it regards the need to translate the overall organization strategy into smaller operational goals, avoiding any bias or incongruence in this process. Therefore, infrastructures under this category are aimed at supporting decentralized sub-goals determination while maintaining an overall strategic vision.
According to the scheme of CI infrastructure decision areas provided by Anand et al.(2009), the decision areas under this category and their relative intents are (Figure 2.4):

- *Organizational direction and CI goals*: facilitating participation of middle- and lower-level managers in the formulation of strategic goals and assure their consistency;

- *Balanced innovation and improvement*: keep up the ability both to innovate and to improve processes, balancing these two activities.

2.4.2 Process

The process category regards the adoption of uniform methods for the discovery and execution of continuous improvement initiatives. The infrastructure of CI has to stimulate people not only to correct process defects, but also to prevent them modifying these processes. The CI infrastructure has also to be concentrated on value-adding processes eliminating waste and adopting a customer-oriented approach. In order to make process changes permanent, the organization has to promote a framework in which standardization is totally embodied in any CI initiative.
The decision areas under the process category are (Figure 2.4):

- *Culture of constant change*: Continually scanning the environment looking for improvement opportunities and challenging the existing way of ding things; training people to remove any fears that may prevent them from suggesting changes;
- *Parallel participation structure*: Lateral structures (e.g. team infrastructures for executing projects) for cross-functional cooperation;
- *Standardized processes*: Standardize processes in order to make CI activities routinized and facilitate experience-learning;
- *Standardized improvement method*: Utilize a standard set of steps for a scientific-approach to CI (e.g. *PDCA* and *DMAIC* cycles):

2.4.3 People

The learning capabilities of individual employees have an impact on organizational dynamic capabilities: they determine an organization’s ability to make changes to its operational processes in response to environmental demands (Ghoshal and Bartlett, 1994; Kraatz and Zajac, 2001). Therefore, under the people category of CI infrastructure decisions we can find all those practices that facilitate organizational learning through individual learning.

The decision areas under the people category are (Figure 2.4):

- *Training and career paths*: Adequate training in the use of scientific methods for problem-solving and for other CI initiatives and define roles, career paths and incentives to motivate employees in CI activities;
- *Information technology support*: Presence of repositories of CI project reports in order to gather information, record and track the results of repeated cycles of knowledge creation (Bendoly and Swink, 2007).

Infrastructure decision area	Empirical observations
Purpose	
Organizational direction and CI goals	Multilevel steering committees with interlinked membership for cascading organizational goals Project selection focused on matching areas of opportunity that the business cares about with improvement frameworks Projects required to have strategic implications 'Y's' relating intended process improvements to organizational goals Governance systems to ensure legitimacy of targets and assess extent of achievement CI initiatives blessed by top management Internal job postings referring to CI initiatives as metric for program relevance Awards for participation and leadership roles in CI
Balanced innovation and improvement	Different project protocols such as Design for Six Sigma, Six Sigma, Lean Projects, and Kaizen Bursts Mistake-proofing features built into processes as part of improvements to ensure long-term and uniform process control
Process	
Constant-change culture	Steering committees encouraging multilevel scanning of external environment External benchmarking through interactions with similar businesses Internal benchmarking through project-tracking databases Voice of the customer, a common feature of process improvement projects Iterations of current and future state value stream maps encouraging sustained emphasis on change CI champions created to act as change agents and to spread CI culture Leadership, team involvement, and change management tools included in CI training
Parallel participation structures	Offline teams headed by team leaders functioning as internal CI methodology experts Use of projects to target specific process improvement goals Built-in adjustments for functional goals to tackle conflicts encountered in projects Special emphasis placed on data to incorporate tradeoffs of functional goals in the interest of organizational performance Supplier involvement in process improvement projects that span organizational boundaries
Standardized processes	Standardization of work practices accomplished and gradually dispersing as a result of process improvement projects Mistake-proofing mechanisms to design out problems
Standardized improvement method	Specified sets of steps to search and implement process improvements "Tollgate reviews" at transitional steps between project stages to ensure compliance
People	
Training and career paths	Systematic initiatives for different levels of training in CI methodology Selection of highly motivated employees as trainees Internal expensing of training to maintain importance of CI methodology training Front-line employees trained to work on improved processes by process improvement project leaders as part of project Specific roles assigned to people with different levels of training in CI methodologies Well defined paths for professional development of full-time CI members Well-defined grades and salary levels in human resource systems for CI participants
Information technology support	Project-tracking software to make real-time progress information available to team members and management Information technology experts frequently included in process improvement teams

Figure 2.4: CI infrastructure decision areas

(Source: *Journal of Operations Management*, 27 (2009) 444–461)

Chapter 3

Structural Equation Modeling

In this chapter the topic of *Structural Equation Modeling (SEM*) will be examined. We will discuss both about *Factor analysis*, that is a way to reduce the amount of data grouping variables into a series of unobserved variables called *factors*, and about the Structural Equation Modeling in a narrow sense, that is the study of the casual relations between unobserved variables. The common purpose of these methods is the effort to reduce the amount of data and to understand the complex relations between variables thanks to the analysis of some unobserved (latent) constructs.

3.1 Historical background

Structural Equation Models (SEM), also known as *ACOVS* (*Analysis of Covariance Structure*) or *LISREL*[6] (*Linear Structural Relations*), were not actually discovered by one or more scientists; they were rather implemented little by little by different researchers who, using different statistical methods, contributed to its definition as we know it nowadays.
The *Linear regression model* was widely utilized before SEM was born. It studies the linear dependencies between one dependent variable and one or more independent variable. Unfortunately it does not help explaining the existence of some unobserved constructs or reducing the amount of data to get to a simpler model.
Charles Sperman (1904-1927) was the first to use the linear correlation coefficient among variables to understand which variables were strictly correlated each other and therefore could be summarized by one single *factor*, thus reducing the data complexity.
But it was only at the beginning of the ‘60s that Structural Equation Models have been properly studied and utilized. In these years, in fact, the Swedish statistician- psychometric

[6] *Lisrel* is also the name of a software for the analysis of structural equation models with latent variables.

Karl Jöreskog first showed a procedure to represent a model based on structural equations, both maintaining the distinction between manifest and latent variables and measuring the casual relations between them. Jöreskog also implemented the *Lisrel* software, whose original purpose was to estimate the coefficients of the factor analysis using the maximum likelihood method. Unlike factor analysis, this new approach carried on by Jöreskog brought two main advantages. First it allowed measurement of variables that were not directly observable since they represent theoretical and non-quantitative concepts, like, in the psychological field, racism, desires, and satisfaction. Second, it provided means to evaluate the hypothesis of causality among these unobserved variables.

Another significant contribute to the development of SEM comes from biometric, particularly from Sewall Wright who first defined *path analysis,* that is a way to identify relations between a set of variables, as well as to quantify the impact on a certain variable through the *path coefficients*.

In 1970 a general formulation of SEM as we know it was provided by Jöreskog in a seminary at Madison University, in the USA. In the following years many articles about SEM and its applications were published, showing the wide utilization perspectives of this technique. Moreover there was a remarkable growth in the number of software available for the numerical analysis of SEM: EQS, AMOS (in association with SPSS), CALIS and so on.

Today Structural Equation Modeling is widely used in many fields (econometric, psychology, sociology, biology, …) and thanks to other correlated techniques (e.g. path analysis, exploratory factor analysis, confirmatory factor analysis, causal models) it represents a valid tool for researchers of every discipline.

3.2 Factor analysis

A fundamental prerequisite for SEM is *Factor Analysis.* It is a statistical method used to describe variability among observed, correlated variables in terms of a lower number of unobserved variables called *factors*. For example, it is possible that variations in four observed variables mainly reflect the variations in two unobserved (also called latent) variables. Factor analysis searches for such joint variations in response to unobserved latent variables. Once the factors have been identified and their connection to the manifest variables has been empirically proved, it is possible to significantly reduce the amount of data and come to a model that is more parsimonious and that provides a better comprehension of the underlying phenomenon.

Factors explaining the manifest variables are extracted through the analysis of the covariance between these variables. Therefore the starting point of the factor analysis is the variance-covariance matrix between the manifest variables, and the point of arrival is the coefficients explaining the relations between manifest and latent variables.

The factor analysis technique implies that every observed variable is modelled as a linear combination of the potential factors, plus an error term. In a mathematical form:

$$\underline{X} = \underline{\Lambda}_x \underline{\xi} + \underline{\delta}$$

In this formula:

$\underline{X}$ is the manifest variables' vector;

$\underline{\Lambda}_x$ is the matrix of factors' coefficients;

$\underline{\xi}$ is the vector of factors;

$\underline{\delta}$ is the vector of error terms.

The assumptions of factor analysis are:

E[$\underline{X}$] = E[$\underline{\xi}$] = E[$\underline{\delta}$] =0 both manifest variables and factors and error terms have average value equal to 0;

E[$\underline{\xi}$ $\underline{\delta}'$]=0 factors and error terms are uncorrelated;

E[$\underline{\delta}$ $\underline{\delta}'$]=0 error terms are uncorrelated each other.

Explaining the above-written formula for every manifest variable X_i we have that:

$$X_i = \lambda_{i1}\xi_1 + \lambda_{i2}\xi_2 + \lambda_{i3}\xi_3 + \cdots + \lambda_{in}\xi_n + \delta_i$$

Mind that:

q = number of variables X;

n = number of factors ξ;
$n < q$

The λ coefficients are called *factor loadings*. It is possible to decompose every equation of X variables in two uncorrelated parts:

$$X_i = c_i + \delta_i$$

Where c_i is the sum of all the factors multiplied by their respective factor loadings, and it's called *common part*:

$$c_i = \lambda_{i1}\xi_1 + \lambda_{i2}\xi_2 + \cdots + \lambda_{in}\xi_n$$

While δ_i is the error component. It is the *unique part*, since it is unique of every X_i and represents the share of variability of X_i that cannot be explained by factors (Corbetta, 2002).

Similarly, it is possible to decompose the variance of every X_i in two components:

$$Var(X_i) = Var(c_i) + Var(\delta_i)$$

Where $Var(c_i)$ is called *common variance*, and $Var(\delta_i)$ is called *unique variance*, or *uniqueness*.

The *common variance* can also be expressed in terms of share of the total variance, and in this case it is called *communality*:

$$\frac{Var(c_i)}{Var(X_i)} = communality$$

Communality of a certain X_i is the percent of variance explained by all the factors jointly, while *unicity* is the remaining part of total variance after that factors explained it. If variables are standardized, communality and uniqueness sum up to 1.

Adopting a factor analysis, everyone has two possible approaches to adopt:

- Exploratory factor analysis (EFA);
- Confirmatory factor analysis (CFA).

3.2.1 Exploratory factor analysis (EFA)

Exploratory factor analysis (EFA) is used to identify interrelationships among manifest variables through a number of latent factors. In this approach the researcher makes no "a-priori" assumptions about relationships among factors and observed variables. In particular, he makes no hypothesis about: the number of factors, relationships among factors, relationships among factors and manifest variables. He, hence, has no idea about the characteristics of the model that is being tested, and he wants to "explore" every possible structure made of different relationships among variables. In the EFA every manifest variable can be explained by every factor, since there are no constrains. We can see a graphical example of a EFA here below (Figure 3.1):

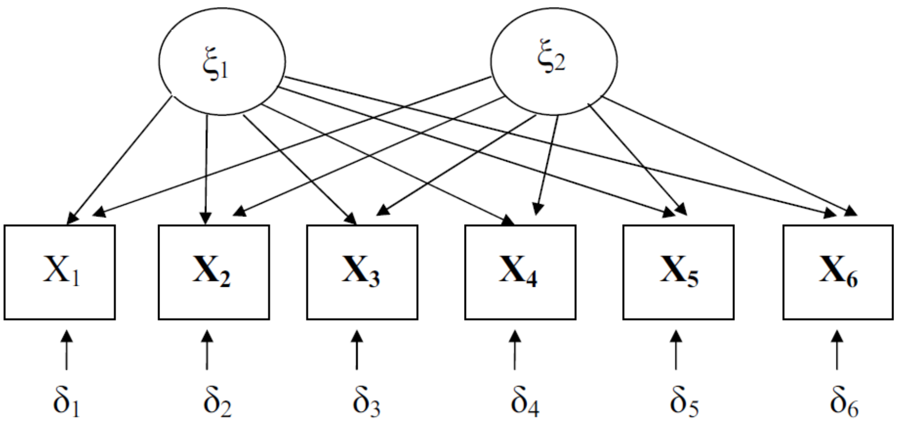


Figure 3.1: Graphical example of EFA: X_i are the manifest variables, δ_i the error terms, and ξ_i the factors. (Source: Corbetta P., *Metodi di analisi multivariate per le scienze sociali*, 2002)

The starting point of the EFA is the variance-covariance matrix of the observed variables. Then, through an appropriate software, factors are estimated (*factor extraction*). To do so, different statistical methods can be applied: Maximum Likelihood, Least Squares, Principal Component Analysis (PCA). At this point the researcher has to choose the appropriate number of factors, assuring that they are enough to explain a good portion of variability, but at the same time in a quantity that allows a parsimonious simplification of the phenomenon. Different methods can be applied to determine the number of factors: Kaiser criterion, variance explained criteria, screeplot, … Once determined how many factors to adopt, it is possible to allocate every variable to its respective factors, checking the factor loadings matrix: every variable is allocated to the factor with the highest factor score coefficient.

Sometimes, however, the estimated loadings from the model can give a large weight on several factors for some of the measured variables, making it difficult to interpret what those factors represent. Therefore, in order to make the output more understandable, the researcher should adopt the so-called “factor rotation”. The goal of factor rotation is to find a solution for which each variable has only a small number of large loadings, that is, is affected by a small number of factors, preferably only one. The observed variables should, therefore, load more strongly on one factor, and much more weakly on the other factors. This is possible because factors geometrically represent a n-dimensional space (*n* is the number of factors), where each of the observed variables represents a point in this space, factor loadings represent the points’ coordinates, and factors represent a coordinate axis. Factor rotation is equivalent to rotating those axis, and computing new loadings in the new rotated coordinate system. There are two main types of factor rotation. Orthogonal rotations (e.g.: Varimax, Quartimax) leave the axis orthogonal and keeps factors uncorrelated each other, while oblique rotations (e.g.: Promax) change the angle between the axis and allows factors to have a certain degree of correlation (Bracalente et al., 2009).

Afterwards, the researcher has to analyse the model to give a logical interpretation to the factors.

Finally, the last step consists of evaluating the model fit. Through a number of indices (that will be shown later) it is possible to assess whether the model adequately fits empirical data.

3.2.2 Confirmatory factor analysis (CFA)

Confirmatory factor analysis (CFA) is a more complex approach aimed at testing a well-defined factor model based on a series of assumptions made by the researcher. It is very common, in fact, that the researchers have in mind an hypothetical structure that he/she wants to test. Those hypothesis can come from previous researches, theoretical issues, sampling methods, or simply from a quick inspection of the variance-covariance matrix of manifest variables. Therefore, in the CFA the number of factors and the relationships between variables are already established. Manifest variables are restricted to load on specific factors. The researcher only wants to test the model and to check, through a series of appropriate indicators, if it fits empirical data.

This approach is widely used after a EFA, in order to evaluate the goodness of the outcomes, based on data.

In the graphical example below (Figure 3.2) we can see a model of CFA: the researcher established through some a-priori assumptions that there are two correlated factors ($\xi_1$and ξ_2) and that X_1, X_2, X_3 and X_4 are influenced by the first factor, while X_5 and X_6 by the second factor.

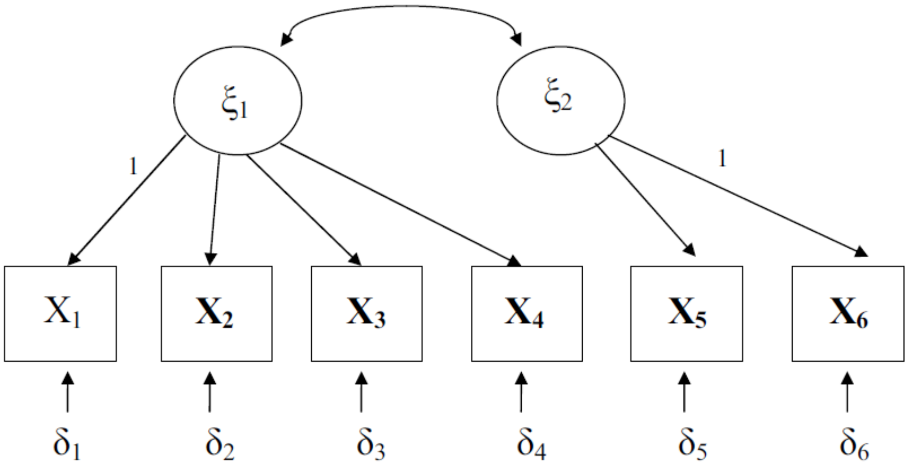


Figure 3.2: Graphical example of CFA. (Source: Corbetta P., *Metodi di analisi multivariate per le scienze sociali*, 2002)

It should be added, however, that there are very often blurred borderlines between exploratory and confirmatory approach to factor analysis. Even a total CFA embodies somehow an exploratory nature. A widely adopted technique consists of splitting the sample in two parts and using the first half to conduct a EFA and the second half for a validation of the model that has been obtained in the previous stage.

3.3 Structural Equation Modeling (SEM)

Structural equation modeling is a technique to specify, estimate, and evaluate models of linear relationships among a set of observed variables (also called measured or manifest) in terms of a generally smaller number of unobserved (latent) variables. The SEM model is an a priori hypothesis about a pattern of linear relationships among observed and unobserved variables. The objective in using SEM is to determine whether this a priori model is valid or not, rather than to find a suitable model (Shah R, Goldstein S.M., 2006).
A SEM model starts from a theoretical relationship model among variables. Subsequently, basing on this model, a theoretical variance-covariance matrix is built, that will be then compared to the variance-covariance matrix of the observed variables, to understand if the model that has been taken in consideration fits the empirical data.
The fundamental set of hypothesis in a SEM model is:

- Continuous and normal variables distributions;
- Linear equations to describe dependencies among variables;
- Randomly-selected sample.

Once appropriately defined the model, it is possible to estimate the latent variables and their relationships.
Every SEM model is made of two sub-models: the measurement model and the structural model. The former allows measurement of unobserved latent variables through a series of observed variables, while the latter describes the casual relationships among latent variables. The model specification in matrix notation is as follows:

$$(1)\quad \underline{\eta} = \underline{\mathrm{B}}\,\underline{\eta} + \underline{\Gamma}\underline{\xi} + \underline{\zeta} \qquad \Big\} \text{ Structural model}$$

$$\left.\begin{aligned} &(2)\quad \underline{Y} = \underline{\Lambda}_y\underline{\eta} + \underline{\varepsilon} \\ &(3)\quad \underline{X} = \underline{\Lambda}_x\underline{\xi} + \underline{\delta} \end{aligned}\right\} \text{ Measurement model}$$

The variables are indicated through the letters x, y, η and ξ. In particular:

y represents the observed endogenous variables[7];

x represents the observed exogenous variables[8];

η represents the latent endogenous variables;

ξ represents the latent exogenous variables.

The error components are indicated through the letters ζ, ε and δ. In particular:

ζ is the error component of η;

ε is the error component of y;

δ is the error component of x.

The structural coefficients are:

B is the coefficient matrix between η and η;

Γ is the coefficient matrix between η and ξ;

Λ_y is the coefficient matrix between η and y;

Λ_x is the coefficient matrix between ξ and x.

Finally we have all the possible variance-covariance matrix:

Φ is the variance-covariance matrix between variables ξ

Ψ is the variance-covariance matrix between the error terms ζ

Θ_ε is the variance-covariance matrix between the error terms ε

Θ_δ is the variance-covariance matrix between the error terms δ

Note that the Ψ matrix plays an important role: it allows to take into account of all the relationships that have been excluded from the model. In almost every case, in fact, there are always some kind of connections among variables that are not specified. Through the Ψ variance-covariance matrix it is possible to explain the effects on the dependant variable of all those variables that have been omitted for some reasons, thus allowing a better specification.

The assumptions of SEM models are:

- All variables are measured in terms of mean deviation, that is:

[7] An *endogenous* variable is a variable generated within a model and, therefore, whose value is determined by one of the functional relationships in that model (it can be both dependent and independent)

[8] An *exogenous* variable is an independent variable that affects a model without being affected by it

$$E[\underline{Y}] = E[\underline{X}] = E\left[\underline{\eta}\right] = E\left[\underline{\xi}\right] = E[\underline{\varepsilon}] = E[\underline{\delta}] = E\left[\underline{\zeta}\right] = 0$$

- Variables are independent and error terms are uncorrelated with variables both within the same equation

$$E\left[\underline{\xi\zeta'}\right] = E\left[\underline{\eta\varepsilon'}\right] = E\left[\underline{\xi\delta'}\right] = 0$$

And between different equations

$$E\left[\underline{\eta\delta'}\right] = E\left[\underline{\xi\varepsilon'}\right] = 0$$

- Error terms of different equations are uncorrelated

$$E\left[\underline{\zeta}\varepsilon'\right] = E\left[\underline{\zeta\delta'}\right] = E[\underline{\varepsilon\delta'}] = 0$$

- Every structural equation has to be non-redundant, namely B has to be a non-singular matrix. This condition assures that no endogenous variable is a linear combination of other endogenous variables.

As previously mentioned, the purpose of Structural Equation Modeling is to compare a theoretical variance-covariance matrix based on the model to the real variance-covariance matrix of the manifest variables (Σ). The theoretical variance-covariance matrix will be obtained from the estimate values of the parameters that make up the model; for this reason we will indicate it with $\Sigma(\theta)$ (and $\Sigma(\hat{\theta})$ its estimate). Therefore, the fundamental equation is:

$$\Sigma = \Sigma(\theta)$$

Where θ is the vector containing all the parameters of the SEM model, $\Sigma(\theta)$ is the variance-covariance matrix written in function of the structural parameters, and Σ is the real variance-covariance matrix.

Unfortunately the above-written equation can be solved only if the model is perfectly specified and if the parameters are all known. Nevertheless, in almost every case the variance-covariance matrix is not available, and the researcher has at his disposal only the sample covariance matrix (S). Moreover, not all the parameters can be identified together. This led to two main problems:

- Model identification: starting from S (or Σ) it is not possible to univocally determinate the parameters of the structural model. Although, given a structural model, it generates one single covariance matrix, it is also true that two different variance-covariance matrix can provide the same SEM parameters estimates. Therefore, further restrictions will be needed to univocally determinate parameters estimates from S (or Σ);
- Estimate: the structural parameters will be estimated so that they minimize the distance between the theoretical covariance matrix $\Sigma(\hat{\theta})$ and the sample covariance matrix S. Therefore the problem lies in finding a mathematical function that minimize the distance between these two matrices, and finally valuate whether the difference between the two matrices is due to the sampling process or to a model misspecification.

There are three possible ways to represent a SEM model:

- System of equations: all the equations composing the structural and measurement model are explained;
- *Path diagram*: graphic representation of the variables and the relationships among them. In particular, manifest variables are shown within a rectangle, latent variables within a circle, while error components are not within any figure. Relationships among variables are represented by arrows (one-directional arrows for casual relations and bidirectional arrows for covariance) and coefficients are shown aside. The absence of any arrow means no relationship between those variables.
- Implicated covariance structure: the model is represented directly explaining the equation $\Sigma = \Sigma(\theta)$.

Let's go now into the two sub-models that make up a SEM model, that is the structural model and the measurement model.

3.3.1 The measurement model

The measurement model analyses dependencies between latent variables and their associated manifest variables, thus "measuring" the model.
It is made of two equations:

(a) $\underline{Y} = \underline{\Lambda_y \eta} + \underline{\varepsilon}$

(b) $\underline{X} = \underline{\Lambda_x \xi} + \underline{\delta}$

The first equation (a) refers to the relationship between latent and manifest endogenous variables. It is composed of: the vector of endogenous manifest variables (Y), the vector of endogenous latent variables (η), the error term of Y (ε), the structural coefficients' matrix (Λ_y) and the variance-covariance matrix of the error term ε (Θ_ε).
The second equation (b) refers to the relationship between latent and manifest exogenous variables. It is composed of: the vector of exogenous manifest variables (X), the vector of exogenous latent variables (ξ), the error term of X (δ), the structural coefficients' matrix (Λ_x) and the variance-covariance matrix of the error term δ (Θ_δ).

3.3.2 The structural model

The structural model deals with the causal relationship between latent variables (both endogenous and exogenous) and therefore represents the "causal" part of the model. It is represented by the equation:

$$\underline{\eta} = \underline{\mathrm{B}\,\eta} + \underline{\Gamma\xi} + \underline{\zeta}$$

It is composed of: the vector of endogenous latent variables (η), the vector of exogenous latent variables (ξ), the error term of η (ζ), the structural coefficients' matrix between η and η (B), the structural coefficients' matrix between η and ξ (Γ), the variance-covariance matrix of ξ (Φ) and the variance-covariance matrix of the error component ζ (Ψ).
Note that the Ψ matrix has zeros in the entire main diagonal, since they represent the regression coefficients of a variable on itself.

3.4 Estimation

After the model has been adequately identified, the following step is the structural parameters estimation. Parameters estimation is done by comparing the actual covariance matrix representing the relationships between variables (S) and the estimated covariance matrix of the model ($\Sigma(\theta)$). This is possible because the covariance matrix of the X and Y variables can be written in terms of the matrices that define the SEM model. Explicating the equations that define the model and using some algebraic calculations, it can be demonstrated that the (symmetric) variance-covariance matrix of the manifest variables X and Y, in the form shown here below:

$$\underline{\Sigma}(\underline{\theta}) = \begin{array}{|c|c|} \hline \underline{\Sigma}_{yy} & \\ \hline \underline{\Sigma}_{xy} & \underline{\Sigma}_{xx} \\ \hline \end{array}$$

Can be written in terms of the model parameters, as follows:

$$
\underline{\Sigma}(\underline{\theta}) = \begin{bmatrix} \underline{\Lambda}_y \, [(\underline{I} - \underline{B})^{-1} \, (\underline{\Gamma} \, \underline{\Phi} \, \underline{\Gamma}' + \underline{\Psi}) \, (\underline{I} - \underline{B})'^{-1}] \, \underline{\Lambda}_y' + \underline{\Theta}_\varepsilon & \\ & \\ \underline{\Lambda}_x \, \underline{\Phi} \, \underline{\Gamma}' \, (\underline{I} - \underline{B})'^{-1} \, \underline{\Lambda}_x' & \underline{\Lambda}_x \, \underline{\Phi} \, \underline{\Lambda}_x' + \Theta_\delta \end{bmatrix}
$$

This complex formula is fundamental, because it allows, once all the parameters of the model are known, to calculate the covariance matrix between the manifest variables (X and Y) starting from the model parameters. In other words, it let us know the covariance matrix that our model implies.

The next problem to face is how to adequately estimate the parameters of our model, in such a way that the "distance" between the actual covariance matrix and the one implied by the model is minimized. This process is possible through the numerical maximization of a fixed criterion. The most widely adopted criterion is the *Maximum Likelihood* (ML). In this approach the matrices of the model can contain either fixed values (that are fixed by the researcher and cannot be modified) or free values (that can change in order to maximize the ML criterion). The bulk of the ML method is trying to estimate the model parameters in a way that the probability that the actual covariance matrix derives from the estimated Σ is maximized. Such probability is determined using a particular statistical distribution called "Wishart's distribution" (we will not go into the description of this distribution, since it is complex and goes beyond the purpose of this work).

Finally, once the free parameters have been estimated, the last step consists of evaluating the difference between the actual covariance matrix and the one implied by the model. If such distance is enough small to be considered due to the sampling process, then the estimation stops; otherwise, through an iterative process, the estimates are furtherly improved. The estimation stops when every step does not bring considerable improvements in the model's fit. If, even after the last step, the distance between the two matrices is too big, then the model has to be rejected.

3.5 Model identification

The analysis of the model identification consists of assessing whether the set of parameters that are going to be estimated uniquely identifies the model; in other words we have to make sure that the same model cannot provide more than one single possible solution. We define a model as “identified” if its parameters are uniquely identified. Generally speaking, in order to demonstrate that a model is identified, the researcher should be able to express all the unknown parameters in terms of the variances-covariances among manifest variables, showing that all the equations are solvable. If this is true, the model is identified. Unfortunately this task is not as easy as it seems: the system of equations is often non-linear and solving it can require a massive amount of calculations.

A necessary (but not sufficient) rule known as “*t-rule*” can help solving this problem. This rule requires that the model does not contain more unknowns than equations, that is that the number of parameters must not exceed the number of variances-covariances among manifest variables. The *t rule* formula is as follows:

$$t \leq \frac{1}{2}(p+q)(p+q+1)$$

Where t is the number of unknown parameters, p is the number of Y variables, and q is the number of X variables. The right part of the formula represents the number of non-redundant elements of Σ.

Actually, applying the *t rule* is equivalent to saying that the number of degrees of freedom has to be non-negative. In a system of equations, in fact, the degrees of freedom are defined as the difference between the number of equations and the number of unknowns. In our case, since we have as many equations as covariances, we have that:

$$\begin{aligned} df &= \text{n. equations} - \text{n. unknowns} \\ &= \text{n. variances/covariances} - \text{n. unknown parameters} \\ &= \frac{1}{2}(p+q)(p+q+1) - t \end{aligned}$$

Therefore saying that $t \leq \frac{1}{2}(p+q)(p+q+1)$ is equal to saying that *degrees of freedom* have to be non-negative.

When the degrees of freedom are zero, the number of free parameters is exactly equal to the number of equations, and the model is said to be "just-identified" or "saturated". Just-identified models provide an exact solution for parameters. But its overall fit cannot be tested, since the S matrix coincides with Σ, and there are no residuals to use for fit tests. Such a model is actually useless, because it is not parsimonious, since it contains the same number of parameters as the variance-covariance matrix.

When the effective number of free parameters is greater than the number of equations, the degrees of freedom are less than zero, and the model is "under-identified" and sufficient information is not available to uniquely estimate the parameters. Under-identified models may not converge during model estimation, and when they do, the parameter estimates they provide are not reliable and overall fit statistics cannot be interpreted. In this case the researcher should reduce the number of unknowns adopting some constraints on the parameters.

For models in which there are fewer unknowns than equations (degrees of freedom are one or greater) the model is "over-identified". An over-identified model is highly desirable because more than one equation is used to estimate at least some of the parameters, significantly enhancing reliability of the estimate (Bollen, 1989). Nevertheless mind that, as previously mentioned, this does not implies that the model is always identified. The condition $df \geq 0$ is a necessary but not sufficient condition for model identification.

Another possible method consists of analyzing model identification in *two steps.* First analyzing identification of the measurement model (as if it were a CFA model), and then of the structural model (as if it were a SEM model with only manifest variables). If the model is identified in both of the two parts, then the overall model is identified; otherwise, if model identification is not accepted in one of the two parts, no conclusions can be drawn. The *two-steps* method for model identification is, indeed, a necessary but not sufficient condition.

A particularly important problem when it comes to model identification is the latent variables' parameterization. Latent variables are, in fact, unobserved and lack of unit of measurement. Therefore it is necessary to fix a metrical parameterization to give sense to numerical relations between latent and manifest variables. There are two mainly adopted criteria for this problem:

- Assign 1 as the value of the latent variables' variance. In this way latent variables result standardized. This criteria is applicable only to latent variables ξ, since the variance of η is not one of the parameters that have to be estimated.
- Assign to the latent variable the same metrical system of one of the manifest variables connected to it (a random one). This implies assigning 1 as the value of the λ that defines the relation between the latent variable and the manifest variable that we chose. Note that this can be valid only for one of the manifest variables related to the latent variable. This criteria can be applied both to variables ξ and η.

These two methods are equivalent and interchangeable. What is fundamental is, once one of the two has been chosen, keep on using it and don't change.

To sum up, the problem of model identification is almost always faced with the help of software. Nevertheless, the researcher has to be completely acknowledged of it since the very first phase of model specification. Using high complex models, with lots of parameters and paths among variables, can often let to model misspecification. For this reason, a highly recommended technique consists of starting from simple models and getting them little by little more sophisticated once the identification has been verified.

3.6 Model fit

Having estimated a model and having verified its identification, it is important to examine the "fit" of an estimated model to determine how well it models the data. Assessing a model's fit is one of the most complicated aspects of SEM because, unlike traditional statistical methods, it relies on non-significance. This means that the "correctness" of a model cannot be tested (there might always be different models that are better than our one), it can only be tested its "non-falsification".

All measures aimed at evaluating model fit are based on the comparison between the sample variance-covariance matrix $\mathbf{S}$ and the variance-covariance matrix implied by our model $\boldsymbol{\Sigma}(\hat{\boldsymbol{\theta}})$ and therefore are based on the residual quantity $\boldsymbol{S} - \boldsymbol{\Sigma}$.

There are different measures to assess model fit, each capturing a different element of the model. The most popular index used to assess goodness of fit is the χ^2- *statistic*. It is based on a specific **T** function that is function of the residual $\boldsymbol{S} - \boldsymbol{\Sigma}$. **T** distribution is a χ^2 with degrees of freedom:

$$df = \frac{1}{2}(p+q)(p+q+1) - t$$

Where *p* is the number of Y variables, *q* is the number of X variables, and *t* is the number of free parameters. The value of this index is confronted with the χ^2distribution; if the null hypothesis is accepted it means that the residual quantity $\boldsymbol{S} - \boldsymbol{\Sigma}$ is enough small to be due to the sampling process and not to a model misspecification.

However, the χ^2- statistic embodies some kind of problems. First of all it is highly influenced by the sample size: if the sample is large, the χ^2 - statistic might lead to the rejection of the tested model, even if it actually fits well the data. Moreover, this index is influenced by the distribution of the observed variables: in particular, if they have high kurtosis (higher than that of a normal-distributed variable), T does not distribute like a χ^2_{df}.

To reduce the effect of sample size some researchers divide the model χ^2 by its degrees of freedom. In this case there seems to be no clear-cut guideline about what value is minimally acceptable; however, values between 1 and 3 are desirable as they indicate reasonable fit.

However, given the above-mentioned problems dealing with the χ^2, other indices have been suggested.

The *Goodness of fit index (GFI)* is calculated standardizing **T** (dividing it by its maximum value):

$$GFI = 1 - \frac{T_i}{\max(T_i)}$$

It varies within the interval [0,1], where 0 means bad model fit and 1 means perfect model fit. GFI is easily interpretable and allows comparisons between different data, but it does not take into account of degrees of freedom. For this reason the *Adjusted goodness of fit index (AGFI)* has been proposed. It is defined as follows:

$$AGFI = 1 - \left(\frac{k}{df}\right)(1 - GFI)$$

Where *df* is the degrees of freedom and *k* is the input variances-covariances. As well as the GFI, the AGFI varies within [0,1]. These indices, however, have a serious drawback: their statistical distribution is unknown and therefore no significance tests can be accomplished.
Another index for evaluating model fit is the *Root mean squared residuals (RMR):*

$$RMR = \sqrt{\frac{1}{k}\sum\left(s_{ij} - \sigma_{ij}\right)^2}$$

It provides the distance between the actual covariance matrix and the one implied by the model in terms of mean squared residuals. It is equal to 0 if the two matrices are identical and grows if the two matrices result more different. Its lower value is 0 but it does not have an upper limit; a *standardized* version of *RMR (SRMR)* is also used: it is calculated using standardized residuals and varies within [0,1]. Values of the SRMR less than 0.10 are generally considered favourable. Also in this case the statistical distribution is unknown.
The *RMSA (Root Mean Square Error of Approximation)* is an index that takes in consideration both the sample size and the parsimoniousness of the model. It is:

$$RMSEA = \sqrt{\frac{Max\left\{F_{min} - \left[\frac{df}{(N-1)}\right], 0\right\}}{df}}$$

Where F_{min} is the minimum possible value of the fitting function (the function that minimize discrepancy between S and Σ), *df* is the degrees of freedom, and *N* is the sample size. RMSEA estimates the amount of error approximation per model degree of freedom, taking sample size into account. Browne and Cudeck (1993) assessed the rules for drawing correct conclusions when using this index:

- $RMSEA \leq 0.05$ indicates close approximate fit
- $0.05 \leq RMSEA \leq 0.08$ suggest reasonable error of approximation
- $RMSEA \geq 0.08$ suggests poor model fit.

The *Comparative fit index (CFI)* and the *Tucker-Lewis index (TLI)* are two of the most used indices that undergo the category of incremental indices. They assess the relative improvement in fit of the model compared with a baseline model, that is typically the independent model (also known as null model) which assumes zero covariances among the observed variables. A rule for the CFI is that values greater than roughly 0.90 may indicate reasonably good fit of the model, while for the TLI values close to 1 are signals of close model fit.

In using SEM it is important to analyze not only the overall model goodness of fit, but also the significance of single parameters or residuals, in order to decide if some of them can be eliminate from the model. Parameters' significance can be tested either with a simple *t-test* , or through the *Square Multiple Correlation Coefficient* (R^2) that show the portion of variance of a manifest variable explained by a specific latent variable.

Another index useful for testing a limited part of the model is the *Modification Indices (MI).* Modification indices report the change in χ^2 that result from freeing fixed parameters. Modifications that improve model fit may be flagged as potential changes that can be made to the model. A high value of the MI for a certain parameter means that, if that parameter were freed, there would be a significant reduction of the χ^2 statistic.

Another aspect worth mentioning talking about model fit regards comparing two different models. For comparing nested models[9] the χ^2statistic can be used. As some parameters are fixed, the model fit to the data usually becomes progressively worse, while as parameters are freed, its fit to the data usually becomes progressively better. The goal is to find a parsimonious model that still fits the data reasonably well. To do so it is necessary to evaluate if the growth in the **T** statistic that results from the "fixing" process of certain parameters is significant or not. Therefore, the distribution of the χ^2 statistic has to be checked, with number of degrees of freedom equal to the difference of the degrees of freedom of the two parameters.

Model comparisons can be also made through two other important indices: *AIC (Akaike Information Criterion*) and *CAIC (Consistent Akaike Information Criterion*). The former is calculated in this way:

$$AIC = c - 2df$$

[9] Two models are *nested* if one is a subset of the other

Where c is the value of the χ^2 statistic and df is the degrees of freedom. The latter is calculated keeping into account of correlations. The best model is usually the one with minor AIC or CAIC. These indices can be used also to evaluate the overall model goodness of fit, because they can compare the actual model with the independent (all variables are independent each other) or with the saturated model (as many variables as many covariances). In addition to Akaike Information Criterion, many software provide also the Schwarz Criterion (SC) and the BIC Criterion. Their application is analogue to the AIC: the smaller the value, the better the fit.

Chapter 4

Data description and factor analysis

In this chapter, after a qualitative and quantitative description of the dataset, the items used for the analysis will be selected; then, some preliminary operations on data will be accomplished, and, finally, exploratory and confirmatory factor analysis will be carried out to pave the way for the future SEM model.

4.1 Data description

The dataset that has been used to accomplish our analysis is the third round of the *High Performance Manufacturing (HPM).* The first round of this project conducted by Roger G. Schroeder and Barbara B. Flynn started in 1989, with the purpose of collecting and analysing data that might explain the reasons why Japanese manufacturing companies (especially in the automobile market) were performing significantly better than many other European and American companies. In particular, researchers were interested to understand if copying the same set of practices/routines of the Japanese could led to the same performance levels. The project raised interest in many other foreign researchers that were willing to cooperate. Data from foreign countries were therefore collected, thus obtaining a broader representation of the manufacturing industrialized world. After the first round a second one began in 1996 and involved a sample of 165 plants in five countries: UK, USA, Germany, Italy and Japan (Flynn and Flynn, 2004). The third round of the HPM project was conducted in 2005 and collected data on a variety of manufacturing practices and performances.

The unit of analysis is the manufacturing plant where lean practices and routines are actually implemented. The sampling process is based on a stratified sample consisting of traditional and high performance manufacturing plants. The list of high performance manufacturing plants was limited to those that had won one or more industry awards.

Traditional plants were randomly selected from ReferenceUSA, a large-scale online business database. In this way it was possible to ensure a sufficient number of high performing plants in the sample along with the more representative traditional plants. Unfortunately, it was not possible to use the same set of plants across different rounds of the HPM project, since some plants were closed over time and some other plants were no longer willing to or able to participate. Therefore, each round of the HPM survey used a different sample of manufacturing plants (Peng et al., 2007).

For the third round data were collected from 2005 to 2007 from 266 manufacturing plants located in nine countries: Finland, USA, Japan, Germany, Sweden, South Korea, Italy, Austria, and Spain; and belonging to three different industries: Electronics, Machinery, Transportation. The distribution of plants by country and by industry is shown in Figure 4.1.

Country	**Industry**			
	Electronics	Machinery	Transportation	Total
Finland	14	6	10	30
USA	9	11	9	29
Japan	10	12	13	35
Germany	9	13	19	41
Sweden	7	10	7	24
South Korea	10	10	11	31
Italy	10	10	7	27
Austria	10	7	4	21
Spain	9	9	10	28
Total	88	88	90	266

Figure 4.1: Plants distribution by country and industry

Once the plants had been identified, their participation to the survey were assured by phone calls and emails. Then, managers of the participating plants each appointed a research coordinator to serve as the link with the HPM research team. The collection of data was made through questionnaires that were sent to the plants along with the instructions in a sealed envelope. Thirteen different questionnaires were directed to 21 informants in each plant (10 managers, 6 supervisors and 5 direct labours). The research coordinator distributed the questionnaires to the named managers and randomly selected workers and supervisors. In return for participating, each plant was provided with a detailed profile of its own manufacturing operations and benchmark data in its industry. With this approach, the third round of the HPM project yielded a response rate of 65% (Peng et al., 2007).

The questionnaires were divided in different areas, each regarding a specific lean technique, or a specific performance. The areas in which the questionnaires were divided are:

- Environment
- Supply chain
- Human resources
- Improvement
- Information system/ Information technology
- Just In Time
- Manufacturing strategy
- Performance
- Quality
- Total Productive Maintenance
- Technology
- New product development.

4.2 Exploratory data analysis

Before going into the analysis of the questionnaires and their relative items, it is necessary to have a look at the sample distribution. In this paragraph we will examine the main characteristics of the respondent plants, such as their dimensions, the countries where they are located, the industry they belong to. This outlook derives from the fact that many researchers have always very clearly underlined the importance of some environmental variables (like the ones we have listed above) in the study of lean techniques within firms, and, in particular, in the analysis of the effects that such techniques lead to.

Let’s then proceed with an exploratory analysis of the sample. The first variable we have to take into account is, of course, the country. Data are collected from 266 plants located in 9 different countries spread all over the world. We can see the distribution of plants by country in the histogram in figure 4.2: the country that is more represented in the survey is Germany (41 plants), followed by Japan (35) and South Korea (31). On the other side, the country with the lowest number of plants is Austria (21). Unfortunately, we are not able to assess which is the country with the highest response rate, since the number of initial questionnaires that have been sent is unknown.

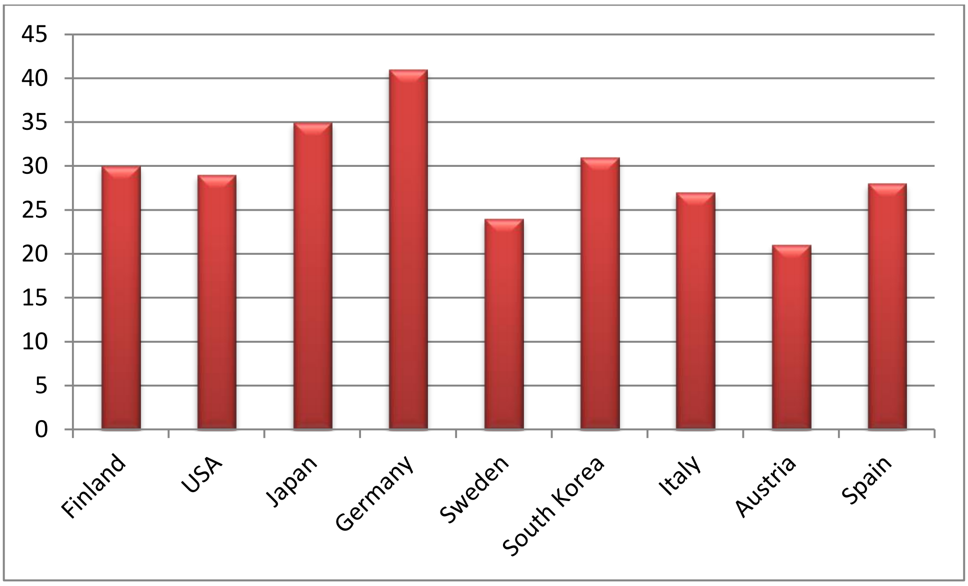


Figure 4.2: Plants distribution by country

For what regards the type of industry, the overall situation looks very homogenous: the number of plants of the three sectors (electronics, machinery, transportation) is almost the same (88 for electronics and machinery, 90 for transportation) (Figure 4.3).

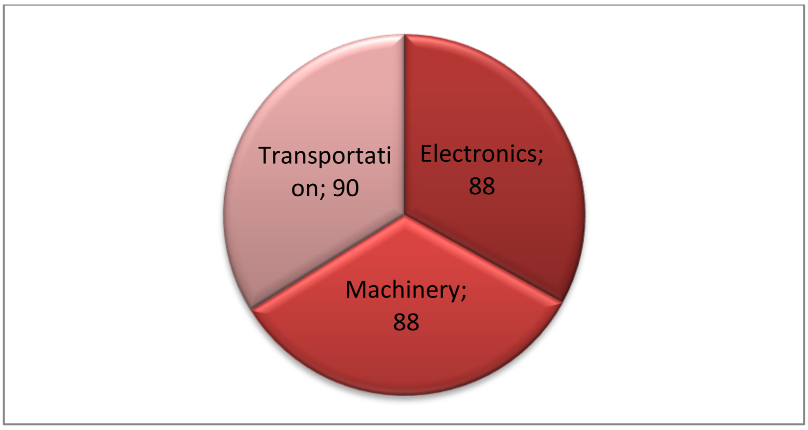


Figure 4.3: Plants distribution by industry

Nevertheless, if we look at the plant distribution both by industry and by country, the situation looks far less homogenous, and there are considerable differences in the number of plants among countries (Figure 4.4). The electronic sector is most highly represented by Finnish plants, while machinery and transportation sectors are more represented in Germany. A remarkably high number of machinery and transportation plants can be seen also for Japan.

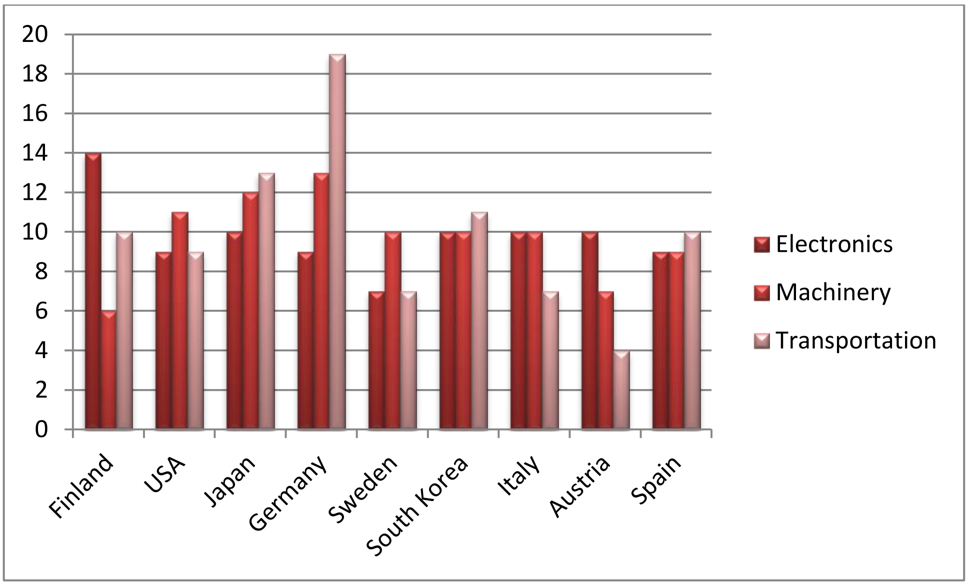


Figure 4.4: Plants distribution by country and by industry

After analysing the country and the industry of the plants of our sample, we should focus on other variables that are important in describing the sample and that significantly influence the adoption of lean techniques. One of these is, for sure, plant dimension. This variable has been studied by looking at the number of employees of every plant. All firms have been categorized in three groups:

- Small-sized plants: those with less than 250 employees;
- Medium-sized plants: those with a number of employees between 250 and 1000;
- Large-sized plants: those with more than 1000 employees.

As we can see in Figure 4.5 the majority of the plants is medium-sized (40% of the sample), whereas there is an 18% of plants that didn't provide this data.

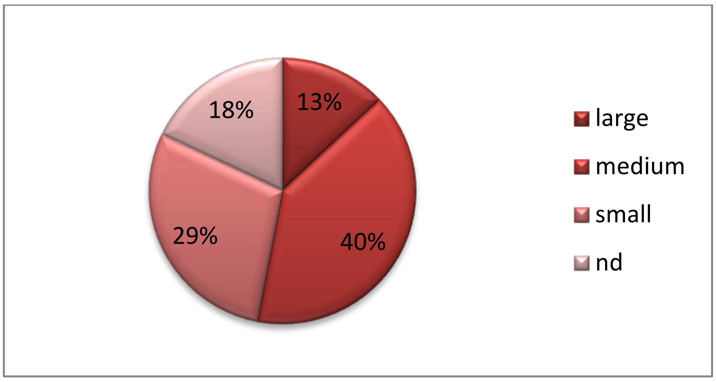
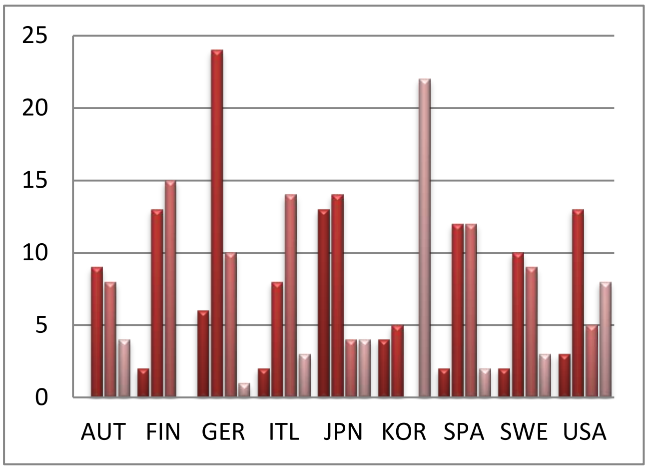


Figure 4.5: Plants distribution by dimensions

In Figure 4.6 and 4.7 there is plants distribution respectively by dimensions and country, and by dimensions and industry, thus allowing comparisons between different countries and industries. Note that large firms are located mostly in Japan and South Korea, medium firms are mostly in Germany and USA, while small firms in some European countries like Finland and Italy. For what regards industries, there seems to be no clear distinction: in each of the three industries large, medium and small plants coexist.



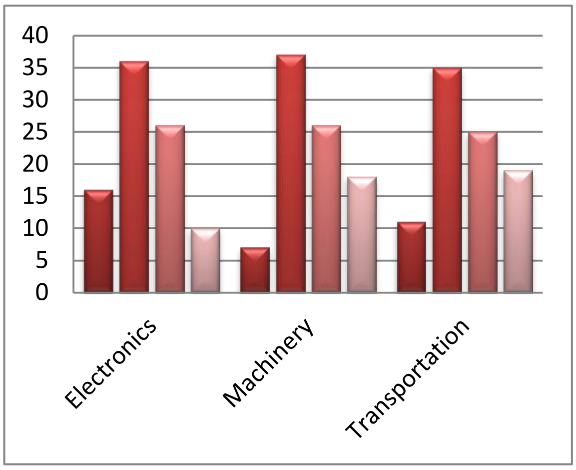


Figure 4.6: Plants distribution by dimensions and country

Figure 4.7: Plants distribution by dimensions and industry

Finally, let's end our descriptive analysis analysing the variable "age". This variable has been calculated as: year of questionnaire filling minus year of firm foundation; and firms have been divided in three categories:

- Young plants: those less than 10 years old;
- Adolescent plants: those between 10 and 20 years old;
- Adult plants: those more than 20 years old.

The majority of the plants (64%) of our sample have been founded more than 20 years ago, whereas adolescent and young plants represent only the 12% and 8% respectively. Also in this case, there is a significant share of the sample that didn't provide this piece of information in the questionnaire (16%).

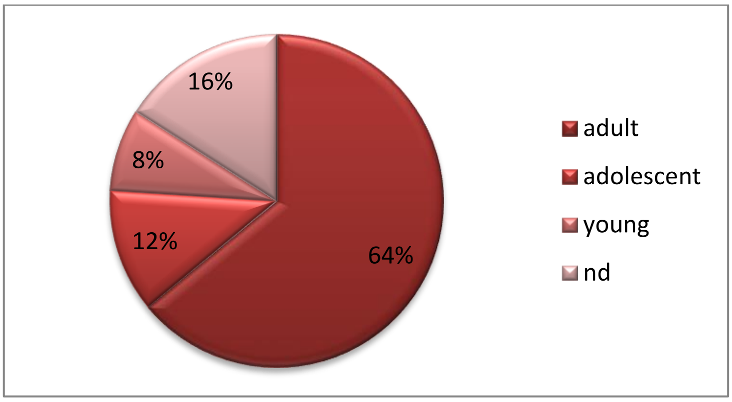
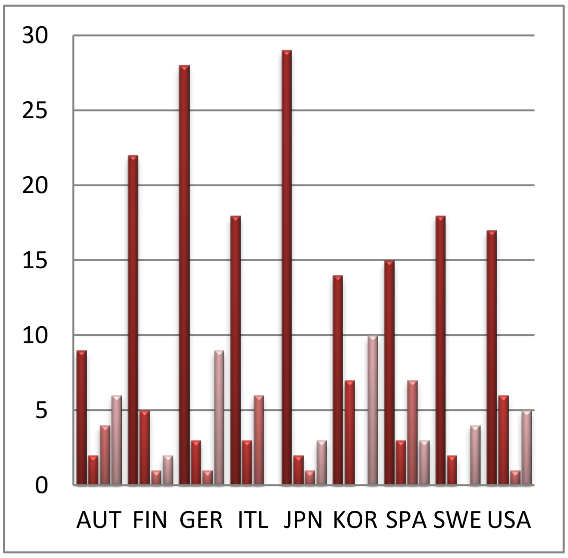


Figure 4.8: Plants distribution by age

If we look at the plants' age by country and industry (Figure 4.9, 4.10) we can see that the oldest plants are located in Germany and Japan, while the youngest ones in Italy and Spain; for the industry we have that the oldest plants are those of the machinery sector, while the youngest belong to the electronic sector, although these distinctions do not emerge very clearly.



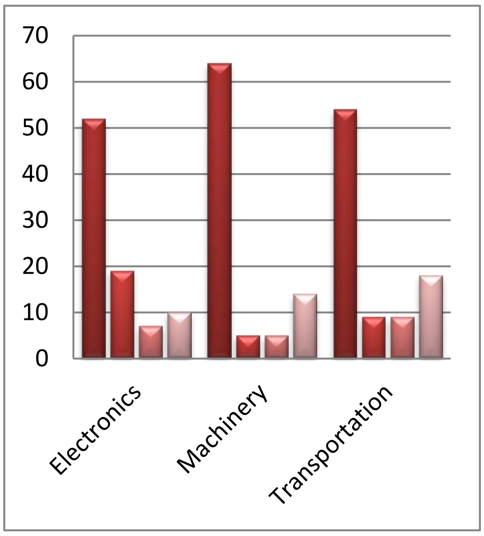


Figure 4.9: Plants distribution by age and country

Figure 4.10: Plants distribution by age and industry

4.3 Item selection

The HPM dataset consists of a large series of items, given to 266 different firms. Although some of these items are in the form of multiple-choice or open questions, the major part are in the form of a seven-level Likert scale (or five-level, sometimes) and these kinds of variables are more interesting to us, given the purpose of our research. The answers of the items vary from 1 to 7, where 1 means a very low level of application of the specific technique (or high disagreement with the sentence of the item) and 7 means very high level of application of that technique (or complete agreement with the sentence of the item). However, some of the items in the dataset don't follow this pattern, but the opposite one: they are, therefore, reverse-scale items. In these cases the value 1 corresponds to a high level of application of that technique, whereas 7 means a low level of application. Fortunately, as we will see later, among the items that have been selected to conduct our analysis there are no reverse-scale items. If some had been, we would have to make a conversion, in order to allow reasonable comparisons between normal and reverse-scale items.

While the sample size is not considerably big (266 plants), the number of variables that have been drawn from the questionnaires is huge. The HPM project provides information about a massive amount of plant details and techniques, especially lean techniques: from *Kanban* system to JIT, from TPM to *Poka-Joke*, and so on. Basically every lean technique that was discussed in the first and second chapters appears in the questionnaire. The reason why the HPM project goes so much into the application of lean techniques is that the aim of the project itself is to describe the diffusion of the "lean thinking" among companies all over the world. To do this, the HPM researchers have adopted a multidimensional approach, analysing all the possible fields in which lean philosophy is rooted. We don't have to forget, in fact, that a powerful impulse for the success of lean techniques comes from the synergetic interplay among different bundles of activities.

With such a high level of variables and a relative small sample size, it was not possible to keep into account all the items, but we needed to do a selection. In particular, we needed to select those items that were strictly related to improvement (and its related routines: process management, leadership involvement, and continuous improvement) and to the elements of the improvement infrastructure: Purpose, Process, and People. The items were selected based on a review of the relevant literature pertaining to manufacturing routines for improvement and its infrastructure (Peng et al., 2007).

So, starting from the complete list of the items, we have selected 13 items that represent in the best way the notion of improvement (and its relative routines). The same procedure was adopted to extract the 29 items of the improvement infrastructure model; in particular, 8 items have been selected for the category "*Purpose*", 12 items for the category "*Process*" and 9 for the category "*People*". The complete scheme of the selected items is shown in Figure 4.11 and 4.12 below. Note that the 42 items, in total, that have been extracted (13+29) still represent a too big amount of variables; however, in the exploratory factor analysis and, most of all, in the confirmatory factor analysis, the number of items will be further reduced to improve model fit, as we will see later.

	Code	**Database code**	**Item**	**Description**	**Meta-routine**
IMPROVEMENT	A	QSPSN06	Statistical techniques to reduce process variance	We make extensive use of statistical techniques to reduce variance in processes	*Process management (PM)*
	B	QSPSN03	Statistical quality control	A large percent of the processes on the shop floor are currently under statistical quality control.	
	C	QSPSN08	Use of control charts	We use charts to determine whether our manufacturing processes are in control	
	D	QSPSN09	Statistical Process Control (SPC)	We monitor our processes using statistical process control	
	E	QSTPN02	provide personal leadership for quality products and quality improvement	Plant management provides personal leadership for quality products and quality improvement	*Leadership involvement (LI)*
	F	QSTPN06	Creation and communication of a vision of quality improvement	Our plant management creates and communicates a vision focused on quality improvement.	
	G	QSTPN07	Management involved in quality improvement projects	Our plant management is personally involved in quality improvement projects	
	H	QSTPN01	Department heads responsible for quality	All major department heads within the plant accept their responsibility for quality	
	I	TSEIN05	Continued learning and improvement	We search for continued learning and improvement, after the installation of new equipment	*Continuous improvement (CI)*
	J	QSVIN03	Performance as a moving target	Continuous improvement makes our performance a moving target, which is difficult for competitors to attack	
	K	QSVIN04	Incremental improvement	We believe that improvement of a process is never complete; there is always room for more incremental improvement	
	L	QSVIN05	Continuous improvement	Our organization is not a static entity, but engages in dynamically changing itself to better serve its customers	
	M	QSVIN01	Dynamic approach	We strive to continually improve all aspects of products and processes, rather than taking a static approach.	

Figure 4.11: Selected items for improvement (and its meta-routines)

	Code	Database code	Item	Description
PURPOSE	Z	SSCSN04	Long-run strategy	I understand the long-run competitive strategy of this plant
	AA	SSCSN01	Communicate strategy	In our plant, goals, objectives, and strategies are communicated to me.
	AB	SSR3N04	Investments consistent with strategy	Potential manufacturing investments are screened for consistency with our business strategy.
	AC	SSR3N05	Manufacturing consistent with strategy	At our plant, manufacturing is kept in step with our business strategy.
	AD	SSVLN03	Long-run focus	We believe that focusing on the distant future will lead to better overall performance than worrying about short-term goals.
	AE	SSFPN04	Strategic plan reviewed and updated	Plant management routinely reviews and updates a long-range strategic plan
	AF	SSINN05	Functions interaction	Our plant's functions work interactively with each other.
	AG	SSINN02	Functions cooperation	The functions in our plant cooperate to solve conflicts between them, when they arise.
PROCESS	AH	HSFLN01	Flat organization	Our organization structure is relatively flat.
	AI	HSHAR03	Freedom in decision-making	This plant is a good place for a person who likes to make his own decisions.
	AJ	HSVCN02	Employees cooperation	We encourage employees to work together to achieve common goals, rather than encourage competition among individuals
	AK	HSDMN02	Communication among departments	Departments in the plant communicate frequently with each other
	AL	HSTMN03	Team creation	Our plant forms teams to solve problems.
	AM	HSTMN09	Team for problem-solving	Employee teams are encouraged to try to solve their own problems as much as possible
	AN	HSVFN05	Management based on facts	In this organization, management is based on facts, not on intuition or tradition
	AO	HSESN02	Encouraging suggestions for improvement	We are encouraged to make suggestions for improving performance at this plant.
	AP	HSIFN02	Ideas exchanging	Our supervisors encourage the people who work for them to exchange opinions and ideas
	AQ	HSIFN01	Encouragement to work as a team	Our supervisors encourage the people who work for them to work as a team.
	AR	SSLFN01	Importance of inter-functional relationships	Our top management emphasizes the importance of good inter-functional relationships
	AS	SSLFN03	Encouraging communication	We are encouraged to communicate well with different functions in this plant.
PEOPLE	AT	HSTWN011	Multiple-tasks training	Our employees receive training to perform multiple tasks.
	AU	HSMFN03	Cross-training	Employees are cross-trained at this plant so that they can fill in for others, if necessary
	AV	HSPCN03	Reward people contribution	Our reward system really recognizes the people who contribute the most to our plant
	AW	HSPCN02	Reward accomplished objectives	The incentive system at this plant is fair at rewarding people who accomplish plant objectives.
	AX	HSPCN04	Incentives for reaching plant goals	The incentive system at this plant encourages us to reach plant goals.
	AY	HSPCN01	Incentives for pursuing plant goals	Our incentive system encourages us to vigorously pursue plant objectives.
	AZ	HSTWN08	Importance of training	Management at this plant believes that continual training and upgrading of employee skills is important.
	BA	HSTWN10	Continuous training	Our employees regularly receive training to improve their skills.
	BB	HSVFN03	Better decisions after training	Our employees will make better decisions if they are trained in data gathering and analysis

Figure 4.12: Selected items for Purpose, Process, and People

In the tables above, under the name “code” there are the letters that identify the different items, and represent the identification system that we will use from now on for our research; under the name “Database code” there is the identification code as it appears in the Codebook of the dataset; under the label “item” there is the title of the item, while under the label “description” there is the sentence of each item as it appears in the original questionnaire. Finally, for the part regarding improvement, there is also, on the very right, a column that identifies the meta-routines of improvement, that is a bundle of different routines that derives from the general notion of improvement, and includes groups of different items. In particular they are: Process Management (PM), Leadership Involvement (LI), ad Continuous Improvement (CI) (see Chapter 2).

4.4 Preliminary data analysis

Before starting doing any kind of analysis regarding Structural Equation Modeling, it is important to check the validity of the data matrix, searching possible out-range or missing values.

While, for the items that were chosen for our research, there is no trace of out-range values (every value is within the interval [1,7]), some missing values have been detected for 16 items. To solve this problem two possible solutions are applicable: the elimination of the statistical unit (the plant, in our case) in which missing values are detected, or the imputation of a plausible value. Since our sample size is not too large, the former solution seems little desirable; we, therefore, chose to adopt the technique of imputation. Since the data matrix at our disposal shows a structure divided by country, and since this variable seems to significantly impact on the effect of lean techniques adoption, we chose to substitute the missing values with the conditional mean by country, in case it is significantly different from the general mean.

We have therefore listed, in Figure 4.13, the variables in which one or more missing values have been detected, and, for each of them, the conditional means by country and the general mean have been calculated for each variable. Then, the values of the F test (for the analysis of the difference of the conditional means) are shown, along with the degrees of freedom.

Variable	Item	FIN	USA	JPN	GER	SWE	KOR	ITL	AUT	SPA	TOT	Observations	F-test	df	p-value
Z	Long-run strategy	5,86	5,25	5,23	5,40	5,42	5,35	4,82	5,64	5,38	5,37	265	4,19	(8;256)	0,0001
AB	Investments consistent with strategy	5,97	5,54	5,84	5,90	5,62	5,49	5,79	6,36	5,96	5,82	263	3,61	(8;254)	0,0005
AC	Manufacturing consistent with strategy	5,67	5,14	5,82	5,50	5,03	5,40	5,69	5,75	5,68	5,53	264	3,91	(8;255)	0,0002
AD	Long-run focus	4,72	4,05	4,77	4,64	5,75	5,33	4,70	5,06	4,79	4,83	264	8,05	(8;255)	0,000
AE	Strategic plan reviewed and updated	5,41	5,41	5,26	5,41	5,41	5,60	5,17	5,71	5,41	5,41	99	1,66	(3;95)	0,1816
AF	Functions interaction	5,45	5,61	5,81	5,14	5,04	5,44	5,51	5,59	5,62	5,46	264	3,76	(8;255)	0,0004
AG	Functions cooperation	5,43	5,43	5,68	5,76	5,34	5,30	5,39	5,73	5,72	5,54	264	2,35	(8;255)	0,0187
AJ	Employees cooperation	5,86	5,93	5,73	5,98	6,03	5,51	5,70	6,15	5,77	5,84	265	3,43	(8;256)	0,0009
AK	Communication among departments	5,53	5,36	5,12	5,42	5,58	5,37	5,15	5,63	5,35	5,38	265	1,67	(8;256)	0,1075
AN	Management based on facts	5,40	5,40	5,29	5,78	4,96	5,22	5,15	5,47	5,59	5,39	261	2,43	(8;252)	0,0151
AO	Encouraging suggestions for improvement	5,58	5,81	5,76	5,55	5,45	5,59	4,77	5,53	5,32	5,50	265	5,6	(8;256)	0,000
AP	Ideas exchanging	5,19	5,51	5,47	5,48	5,72	5,17	4,83	5,66	5,30	5,36	265	5,58	(8;256)	0,0000
AQ	Encouragement to work as a team	5,22	5,70	5,35	5,41	5,80	5,32	4,95	5,53	5,47	5,40	265	3,54	(8;256)	0,0007
AR	Importance of inter-functional relationships	5,58	5,52	5,62	5,84	5,58	5,67	5,49	5,99	5,72	5,67	264	1,1	(8;255)	0,3635
AS	Encouraging communication	5,23	5,78	5,67	5,63	5,50	5,38	5,61	5,56	5,74	5,57	264	1,57	(8;255)	0,1334
BB	Better decisions after training	6,05	6,04	5,10	4,71	5,21	5,56	5,78	4,87	5,71	5,42	258	9,6	(8;249)	0,000

Figure 4.13: F-test for evaluating the significant difference of conditional means by country

For those items where the F-test suggested that conditional means by country were significantly different, at 0.05 level, from the general mean, the missing values were substituted with the conditional mean (not-enlightened p-values in the table); while, if conditional means were not significantly different from the general mean, missing values of that item were substituted with the general mean (enlighten p-values in the table).

At this point, a further observation has to be made. Table 4.13 reports also the number of observations for every variable where missing values have been detected. While for the majority of these variables, the number of observation is little less than 266 (meaning a restricted number of missing values), there is one variable where observations are too little: for variable AE ("*Strategic plan reviewed and updated"*) the number of observation is only 99. This means that there are 167 missing values, so the number of missing values is much bigger than the number of observations. It looks obvious, then, that such a variable, with such a high number of missing data, is useless for any kind of statistical analysis. By substituting missing values with the general mean, the outcomes would be that for almost every plant the value of the variable AE would be pretty much the same (equal to the average value of the 99 data). Therefore, it was immediately decided to drop this variable from the dataset, and focusing on the remaining variables.

After "cleaning" the data matrix, we started looking at the main summary and descriptive statistics for the variables in question. In Tables 4.14 and 4.15 mean, median, standard deviation, minimum value, maximum value, skewness and kurtosis were calculated for each variable, both for Improvement and for Purpose-Process-People.

	Variable	Item	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
IMPROVEMENT	A	Statistical techniques to reduce process variance	4,50	4,51	1,07	2	7	-0,07	2,47
	B	Statistical quality control	4,75	4,895	1,16	1,73	6,93	-0,36	2,48
	C	Use of control charts	4,83	5	1,08	1,93	6,9	-0,43	2,73
	D	Statistical Process Control (SPC)	4,72	4,73	1,21	1,67	6,96	-0,40	2,54
	E	provide personal leadership for quality products and quality improvement	5,69	5,67	0,73	3,67	7	-0,37	2,74
	F	Creation and communication of a vision of quality improvement	5,56	5,67	0,87	3	7	-0,72	3,26
	G	Management involved in quality improvement projects	5,67	5,67	0,79	2,33	7	-0,80	3,97
	H	Department heads responsible for quality	5,83	6	0,74	3	7	-0,80	3,72
	I	Continued learning and improvement	5,51	5,53	0,71	3	7	-0,42	3,03
	J	Performance as a moving target	5,22	5,395	0,88	2,63	6,92	-0,69	2,98
	K	Incremental improvement	6,09	6,155	0,50	4	7	-0,87	4,42
	L	Continuous improvement	5,47	5,5	0,64	3,58	7	-0,22	2,64
	M	Dynamic approach	5,51	5,6	0,69	3,27	7	-0,47	3,08

Figure 4.14: Summary and descriptive statistics for items of the category Improvement

	Variable	Item	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
PURPOSE	Z	Long-run strategy	5,37	5,42	0,77	1,94	6,88	-0,77	4,37
	AA	Communicate strategy	5,58	5,67	0,76	2,67	7	-0,79	3,71
	AB	Investments consistent with strategy	5,82	6,00	0,72	3,33	7	-0,85	3,53
	AC	Manufacturing consistent with strategy	5,53	5,67	0,76	3,33	7	-0,63	3,18
	AD	Long-run focus	4,84	5,00	0,95	2	7	-0,39	3
	AF	Functions interaction	5,46	5,67	0,72	2,67	7	-0,69	3,85
	AG	Functions cooperation	5,54	5,67	0,68	3,33	7	-0,54	3,38
PROCESS	AH	Flat organization	4,62	4,60	1,02	2	7	0,03	2,48
	AI	Freedom in decision-making	3,60	3,58	0,72	1	5,89	-0,17	3,53
	AJ	Employees cooperation	5,84	5,92	0,57	3,89	7	-0,69	4
	AK	Communication among departments	5,38	5,50	0,72	3	7	-0,45	3,32
	AL	Team creation	5,24	5,37	0,90	1,33	7	-0,71	3,64
	AM	Team for problem-solving	5,11	5,15	0,76	3,21	7	-0,10	2,77
	AN	Management based on facts	5,38	5,50	0,88	2	7	-0,83	4,29
	AO	Encouraging suggestions for improvement	5,50	5,67	0,73	3,11	7	-0,75	3,36
	AP	Ideas exchanging	5,36	5,40	0,64	3,67	6,9	-0,25	2,56
	AQ	Encouragement to work as a team	5,41	5,44	0,71	2,67	6,87	-0,63	3,85
	AR	Importance of inter-functional relationships	5,67	5,67	0,79	2,33	7	-0,84	4,3
	AS	Encouraging communication	5,57	5,67	0,77	3	7	-0,92	4,18
PEOPLE	AT	Multiple-tasks training	5,21	5,33	0,82	2,67	7	-0,42	3,16
	AU	Cross-training	5,20	5,33	0,75	2,5	7	-0,61	3,54
	AV	Reward people contribution	4,12	4,20	1,08	1	7	-0,27	2,72
	AW	Reward accomplished objectives	4,35	4,50	1,11	1	7	-0,49	3,22
	AX	Incentives for reaching plant goals	4,46	4,60	1,14	1	7	-0,46	3,07
	AY	Incentives for pursuing plant goals	4,36	4,42	1,15	1	7	-0,24	2,94
	AZ	Importance of training	5,72	5,78	0,73	2,67	7	-0,89	4,02
	BA	Continuous training	4,98	5,00	0,88	2,67	7	-0,28	2,61
	BB	Better decisions after training	5,43	5,50	0,98	2	7	-0,76	3,7

Figure 4.15: Summary and descriptive statistics for items of the categories Purpose, Process, People

We can immediately observe that for almost every variable, in both of the two groups, the average values, as well as the medians, are higher than the average values of a generic 7-levels Likert scale (that is 4). This fact means that, in the manufacturing firms of our sample, the lean techniques that the items refer to are strongly embraced.

Finally, in order to allow reasonable comparisons among different items and to avoid that different average values or levels of variability could lead to misleading conclusions, every variable was standardized. The standardization process that was adopted consists of a two-stages standardization:

- A first standardization made by *country:* every value was standardized using mean and standard error of the country the specific item referred to:

$$W_{ij} = \frac{X_{ij} - \overline{X^C{}_j}}{\sigma^C{}_j}$$

In this formula X_{ij} is the single value that plant *i* (*i* =1,…,266) assigned to the item *j* (*j*=1,…,54), $\overline{X^C{}_j}$ is the conditional expected value of the item *j* calculated considering just the plants located in the same country as plant *i*, while $\sigma^C{}_j$ is the standard deviation of the item *j* calculated considering just the plants located in the same country as plant *i*.

- A second standardization by *industry*: the values of the first standardization were further standardized using mean and standard error of the industry the specific item referred to:

$$Z_{ij} = \frac{W_{ij} - \overline{X^I{}_j}}{\sigma^I{}_j}$$

In this formula W_{ij} is the value of plant *i* and item *j* after the first standardization, $\overline{X^I{}_j}$ is the conditional expected value of the item *j* calculated considering just the plants of the same industry as plant *i*, while $\sigma^I{}_j$ is the standard deviation of the item *j* calculated considering just the plants of the same industry as plant *i*.

In Figure 4.16 and 4.17 we can have a look at the descriptive statistics of the variables after the two-stages standardization.

	Variable	Item	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
IMPROVEMENT	A	Statistical techniques to reduce process variance	0,00	-0,02	1,00	-2,69	2,48	-0,04	2,43
	B	Statistical quality control	0,00	0,01	1,00	-2,75	2,24	-0,24	2,62
	C	Use of control charts	0,00	0,02	1,00	-3,36	2,31	-0,51	3,06
	D	Statistical Process Control (SPC)	0,00	0,12	1,00	-2,71	2,12	-0,32	2,50
	E	provide personal leadership for quality products and quality improvement	0,00	0,06	1,00	-3,19	2,02	-0,34	2,66
	F	Creation and communication of a vision of quality improvement	0,00	0,19	1,00	-2,93	1,85	-0,65	2,90
	G	Management involved in quality improvement projects	0,00	0,13	1,00	-3,79	2,20	-0,57	3,56
	H	Department heads responsible for quality	0,00	0,14	1,00	-2,80	2,17	-0,50	2,99
	I	Continued learning and improvement	0,00	0,12	1,00	-2,79	2,18	-0,42	2,78
	J	Performance as a moving target	0,00	0,19	1,00	-3,04	2,35	-0,33	2,92
	K	Incremental improvement	0,00	0,14	1,00	-3,13	1,85	-0,74	3,22
	L	Continuous improvement	0,00	0,11	1,00	-3,04	2,57	-0,32	2,93
	M	Dynamic approach	0,00	0,05	1,00	-2,79	2,47	-0,22	2,76

Figure 4.16: Summary and descriptive statistics for standardized variables of the category Improvement

	Variable	Item	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
PURPOSE	Z	Long-run strategy	0,00	0,09	1,00	-3,75	3,04	-0,60	3,68
	AA	Communicate strategy	0,00	0,23	1,00	-3,73	2,42	-0,77	3,70
	AB	Investments consistent with strategy	0,00	0,11	1,00	-3,03	1,86	-0,63	3,05
	AC	Manufacturing consistent with strategy	0,00	0,09	1,00	-3,03	2,45	-0,32	2.99
	AD	Long-run focus	0,00	-0,02	1,00	-3,01	2,61	-0,30	2,84
	AF	Functions interaction	0,00	0,08	1,00	-3,24	2,60	-0,36	3,09
	AG	Functions cooperation	0,00	0,04	1,00	-3,18	2,32	-0,46	3,18
PROCESS	AH	Flat organization	0,00	0,03	1,00	-2,42	2,69	0,00	2,68
	AI	Freedom in decision-making	0,00	0,04	1,00	-3,51	2,98	-0,32	3,37
	AJ	Employees cooperation	0,00	0,13	1,00	-3,06	2,82	-0,59	3,23
	AK	Communication among departments	0,00	0,04	1,00	-3,15	2,50	-0,39	3,03
	AL	Team creation	0,00	0,04	1,00	-3,66	2,08	-0,59	3,31
	AM	Team for problem-solving	0,00	0,13	1,00	-2,70	2,26	-0,24	2,61
	AN	Management based on facts	0,00	0,19	1,00	-3,45	2,81	-0,69	3,71
	AO	Encouraging suggestions for improvement	0,00	0,14	1,00	-3,04	2,16	-0,41	2,80
	AP	Ideas exchanging	0,00	0,01	1,00	-2,60	2,67	-0,13	2,38
	AQ	Encouragement to work as a team	0,00	0,02	1,00	-2,94	2,22	-0,39	3,01
	AR	Importance of inter-functional relationships	0,00	0,11	1,00	-3,26	2,04	-0,64	3,31
	AS	Encouraging communication	0,00	0,16	1,00	-3,36	2,12	-0,78	3,61
PEOPLE	AT	Multiple-tasks training	0,00	0,08	1,00	-3,06	2,23	-0,41	3,07
	AU	Cross-training	0,00	0,15	1,00	-2,66	2,34	-0,44	2,66
	AV	Reward people contribution	0,00	0,00	1,00	-2,72	2,26	-0,15	2,61
	AW	Reward accomplished objectives	0,00	0,07	1,00	-3,00	2,08	-0,34	2,66
	AX	Incentives for reaching plant goals	0,00	0,01	1,00	-2,90	2,08	-0,19	2,51
	AY	Incentives for pursuing plant goals	0,00	-0,02	1,00	-2,98	2,39	-0,10	2,55
	AZ	Importance of training	0,00	0,18	1,00	-3,12	1,84	-0,64	3,07
	BA	Continuous training	0,00	-0,01	1,00	-2,86	2,21	-0,32	2,62
	BB	Better decisions after training	0,00	0,13	1,00	-3,06	2,13	-0,50	2,91

Figure 4.17: Summary and descriptive statistics for standardized variables of the categories Purpose, Process, People

4.5 Exploratory factor analysis

What has been done in the last two paragraphs of this chapter was to reduce the massive amount of variables of the dataset to come to a smaller and easier-to-manage set of variables. Each of these variables, that, as we've already said, are nothing but the items of the questionnaire of the HPM project, represents a specific *lean* technique, or even an aspect of a technique. Although, of course, there are not two or more items that are exactly equal one another or that measure exactly the same aspect of a lean technique, there are many items that are strictly related each other. Indeed, the structure of the questionnaires of the HPM project is made in a way that, for one lean technique, more than one items are needed. It looks reasonable, therefore, to group these items under one larger construct that comprehends them. Moreover, even if there are items that measure two different lean techniques, in many cases adopting one lean technique intrinsically implies adopting another one. We, therefore, need to create these bundles of lean activities in order to keep into account of those techniques that are strictly related one another and that it's likely they will be adopted together within the firm. This idea of grouping different activities (or aspects of the same activity) into one or more larger constructs perfectly fits into the notion of capability as a bundle of interrelated routines, that we have been discussing in the second chapter. Thanks to this process, it is possible to reduce the 41 variables at our disposal and come to a significantly smaller number of elements that will be helpful to provide significance to the statistical model that will be examined.
As the reader might have noticed, this item-grouping process has already taken place. Selecting the two groups of items, in fact, they have been divided into respectively: the three elements of Continuous Improvement infrastructure (Purpose, Process, and People) and into the three meta-routine of Improvement (Process Management, Leadership Involvement, and Continuous Improvement) (see Figure 4.11 and 4.12). As it was explained in the second chapter, the three elements of CI infrastructure consist of:

- *Purpose*: it covers the formulation and communication of organizational and project goals for CI, translating the overall organization strategy into smaller operational goal and supporting decentralized sub-goals determination;

- *Process*: regards the adoption of uniform methods for the discovery and execution of continuous improvement initiatives at process level (modify and correct processes, focus on value-adding activities, …);
- *People*: comprehends those practices that facilitate organizational learning through individual learning.

While the three meta-routines underlying Improvement consist of:

- *Process Management*: involves efforts to map and improve organizational processes through cost reduction and more efficiency;
- *Leadership Involvement*: aims at stimulating improvement capabilities through leadership involvement at all levels of the organization, motivating employees' participation in improvement activities;
- *Continuous Improvement*: refers to sustained incremental improvements of existing products/processes, modifying and refining them.

However, allocating items to these categories, we based purely on theory, in particular on a review of the relevant literature about improvement initiatives and CI infrastructures. What we need to do now is to check if the data provided by the questionnaires of the HPM project fits this theoretical structure. We, therefore, need to set off a factor analysis (first exploratory and then confirmatory) to assess if the item division that our literature suggests is confirmed by data at our disposal.

In the exploratory factor analysis we take the 13 items regarding improvement and the 28 items regarding its infrastructural elements and try to explore if there could be one or more latent (i.e. not measured) factors that can summarize them, thus coming to a more parsimonious model. In this step, no assumptions are made on the number of these factors or the strength of the relations with the measured items.

What we expect to find out, is that:

- The group of 28 items could be summarized by 3 latent factors, corresponding to the Purpose-Process-People groups;

- The group of 13 items could be summarized by 3 latent factors, corresponding to the three meta-routines of Improvement: Process Management, Leadership Involvement, and Continuous Improvement.

4.5.1 Purpose, Process, People

Starting from the 28 items of the CI infrastructure, the first step to take is to calculate the variance-covariance matrix of these variables. In this matrix (displayed in Appendix A1) we can detect some high correlation values, especially for those items that should be grouped under the same construct.

Afterwards, it is time to estimate a factor analysis model for the variables in question[10], using the maximization method of Maximum Likelihood. If no restrictions on the maximum number of factors are set, the software automatically adjusts it to 20 factors. Nevertheless, in our case, a factor analysis model with so many factors is not valid: 20 factors are actually too many to extract, and the size of the sample does not justifies such a big number. This fact, that often led to some kind of estimation problems, is quite frequent in factor analysis estimation procedures, and goes under the name of *Heywood Case*[11]. Therefore, to overcome this problem, a factor analysis model has been estimated fixing the maximum number of factors to 5. The output of the software is displayed below.

[10] For the exploratory and confirmatory factor analysis, as well as for all the future analysis regarding SEM, the software that has been used is Stata (12).

[11] Technically, a *Heywood case* occurs in factor analysis when the iterative maximum likelihood estimation method converges to variance values that are less than a prefixed lower bound value, for example less than zero, or correlation estimates greater than 1 in absolute value.

```
Factor analysis/correlation                        Number of obs    =      266
    Method: maximum likelihood                     Retained factors =        5
    Rotation: (unrotated)                          Number of params =      130
                                                   Schwarz's BIC    =  1153.69
    Log likelihood = -213.9192                     (Akaike's) AIC   =  687.838
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	9.14634	7.30160	0.6604	0.6604
Factor2	1.84474	0.33267	0.1332	0.7936
Factor3	1.51208	0.67040	0.1092	0.9028
Factor4	0.84168	0.33773	0.0608	0.9636
Factor5	0.50395	.	0.0364	1.0000

```
    LR test: independent vs. saturated: chi2(378) = 3709.65 Prob>chi2 = 0.0000
    LR test:   5 factors vs. saturated: chi2(248) =  406.12 Prob>chi2 = 0.0000
```

The first column of the table shows the eigenvalues of the five factors, the second column the difference between each eigenvalue and the previous one, the third shows the proportion on the sum of the eigenvalues, and the last one the cumulative sum of eigenvalues. Obviously, Stata provides also the table of the factor loadings; however, in this phase it is not interesting to us, first because factors are still unrotated (and therefore uninterpretable), and also because we want first to understand which is the most appropriate number of factors to use; after this, the table of the (rotated) factor loadings will be discussed. So, how many factors? To answer this question, statistical literature provides a series of criterion, that can be used along with some a-priori theoretical hypothesis on the topic under analysis. One of the most used is the Kaiser criterion: it assesses that the appropriate number of factors to be retained is equal to the number of factors whose eigenvalues are greater than 1. In this case, we have that for the first three factors eigenvalues are greater than 1 (9.15, 1.84, 1.51), while for the fourth and fifth factors eigenvalues are smaller than 1 (0.84, 0.50). Therefore, Kaiser Criterion suggests that the number of factors should be 3.

It was then estimated a factor model fixing the maximum number of factors to 4, but no relevant differences with the previous case with 5 factors were spotted. Kaiser Criterion still suggests 3 factors, and the values of the eigenvalues are quite equal to the previous ones. The outcome is displayed here below.

```
Factor analysis/correlation                        Number of obs    =      266
    Method: maximum likelihood                     Retained factors =        4
    Rotation: (unrotated)                          Number of params =      106
                                                   Schwarz's BIC    =   1111.4
    Log likelihood = -259.7744                     (Akaike's) AIC   =  731.549

    --------------------------------------------------------------------------
         Factor  |   Eigenvalue   Difference        Proportion   Cumulative
    -------------+------------------------------------------------------------
        Factor1  |      9.11512      7.27352            0.6868       0.6868
        Factor2  |      1.84160      0.36698            0.1388       0.8256
        Factor3  |      1.47462      0.63475            0.1111       0.9367
        Factor4  |      0.83987            .            0.0633       1.0000
    --------------------------------------------------------------------------
    LR test: independent vs. saturated: chi2(378) = 3709.65 Prob>chi2 = 0.0000
    LR test:   4 factors vs. saturated: chi2(272) =  494.48 Prob>chi2 = 0.0000
```

It was, then, estimated another factor model with the constraint of having not more than 3 factors, and again all of them show eigenvalues greater than 1. The outcome is displayed below.

```
Factor analysis/correlation                        Number of obs    =      266
    Method: maximum likelihood                     Retained factors =        3
    Rotation: (unrotated)                          Number of params =       81
                                                   Schwarz's BIC    =  1119.71
    Log likelihood = -333.7234                     (Akaike's) AIC   =  829.447

    --------------------------------------------------------------------------
         Factor  |   Eigenvalue   Difference        Proportion   Cumulative
    -------------+------------------------------------------------------------
        Factor1  |      9.04692      7.17634            0.7293       0.7293
        Factor2  |      1.87058      0.38258            0.1508       0.8801
        Factor3  |      1.48799            .            0.1199       1.0000
    --------------------------------------------------------------------------
    LR test: independent vs. saturated: chi2(378) = 3709.65 Prob>chi2 = 0.0000
    LR test:   3 factors vs. saturated: chi2(297) =  636.92 Prob>chi2 = 0.0000
```

Another decision criterion that can be taken into account while choosing the number of factors is the scree plot of eigenvalues. It consists of representing in a graph of Cartesian axis the factors and their respective eigenvalues: on the Y axis there are the eigenvalues of the factors, and on the X axis their order of extraction. Connecting the dots of the graph, a line will appear. The scree plot criterion assesses that the appropriate number of factors should be the one in correspondence of which the line starts becoming flat, almost parallel to the horizontal axis (Bracalente et al., 2009). In Figure 4.18 the scree plot of eigenvalues (with no restrictions on the maximum number of factors) is displayed: it can be observed that after the third factor, the line of the eigenvalues starts smoothing, and becoming flat, coming progressively closer to the horizontal axis.

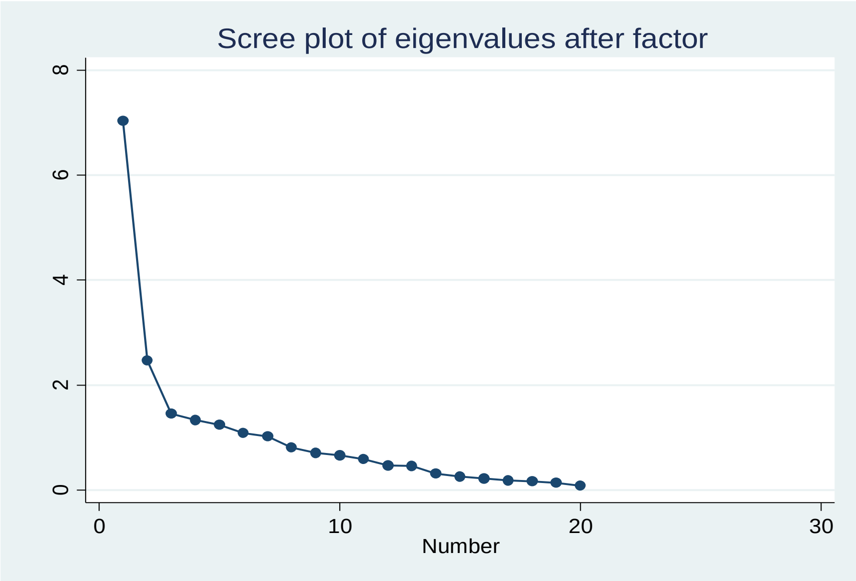


Figure 4.18: Scree plot of eigenvalues for factor analysis of Purpose-Process-People

Having determined that the appropriate number of factor should be 3, it is time to go deeper and have a look at the matrix of the factor loadings provided by the model. Taking the last estimated model (the one with the condition of maximum 3 factors) as the definitive model, we could easily look at the factor loading matrix that is provided as output of the estimates, under the table of eigenvalues. However, as it has already been specified, these factors are unrotated, and therefore the factor loading matrix gives high weights to the first factor for many of the variables, thus making the output not understandable. In order to overcome this problem, factors need to be rotated. Among all the possible choices of factor rotation it was chosen the Promax rotation: it looked appropriate in our case because it is an oblique rotation, and therefore implies a certain degree of correlation among factors. It is reasonable, in fact, to assume that the three categories in which these variables are grouped, somehow influence each other. Here below (Figure 4.19) the table of rotated factor loadings is displayed, along with the values of uniqueness (last column on the right).

Rotated Factor loadings (pattern matrix) and unique variances					
Variable	Item	Factor 1	Factor 2	Factor 3	Uniqueness
Z	Long-run strategy	0.5006	0.0611	0.1861	0.5525
AA	Communicate strategy	0.5338	0.1057	0.0665	0.5823
AB	Investments consistent with strategy	0.0301	0.7139	-0.0126	0.4734
AC	Manufacturing consistent with strategy	0.0289	0.7331	-0.0184	0.4510
AD	Long-run focus	-0.0824	0.2179	0.0653	0.9541
AF	Functions interaction	0.0482	0.6958	-0.0181	0.4874
AG	Functions cooperation	0.0008	0.8048	-0.0968	0.4261
AH	Flat organization	0.2675	0.1347	0.0230	0.8558
AI	Freedom in decision-making	-0.4170	-0.0681	-0.1283	0.6987
AJ	Employees cooperation	0.2826	0.2674	0.0290	0.7388
AK	Communication among departments	0.2489	0.2445	0.1482	0.7007
AL	Team creation	0.6329	0.0529	-0.0702	0.6076
AM	Team for problem-solving	0.7166	-0.0329	-0.2082	0.6383
AN	Management based on facts	-0.0374	0.3475	0.0966	0.8523
AO	Encouraging suggestions for improvement	0.6926	-0.0096	-0.0226	0.5459
AP	Ideas exchanging	0.7456	0.0256	-0.0371	0.4526
AQ	Encouragement to work as a team	0.7911	0.0489	-0.1575	0.4550
AR	Importance of inter-functional relationships	-0.0353	0.6629	0.0878	0.5207
AS	Encouraging communication	-0.0132	0.7422	0.0881	0.3841
AT	Multiple-tasks training	0.5458	-0.0921	0.2360	0.5706
AU	Cross-training	0.5097	-0.0510	0.1699	0.6477
AV	Reward people contribution	-0.0161	0.0721	0.7366	0.4101
AW	Reward accomplished objectives	-0.0770	-0.0105	0.9342	0.2154
AX	Incentives for reaching plant goals	-0.0597	-0.0142	0.9299	0.2099
AY	Incentives for pursuing plant goals	-0.0016	-0.0357	0.9060	0.2143
AZ	Importance of training	0.5178	-0.0199	0.2574	0.5265
BA	Continuous training	0.4943	-0.0015	0.3250	0.4628
BB	Better decisions after training	0.0161	0.1512	0.0584	0.9600

Figure 4.19: Rotated factor loadings and uniqueness for factor analysis of Purpose-Process-People (1)

For every variable, the highest factor loadings among the three factors has been enlightened in red (in some cases there are two enlightened values for the same variable), because every variable has to be located to the factor with the highest weight. It can be assessed that the loadings seems to distribute quite well among the three factors: for almost every variable there is a significant gap between the highest weight and the other two weights. Nevertheless the division seems not to perfectly reflect the assumptions based on theory (see Figure 4.12). Furthermore, there are some variables (the ones whose rows are blue-enlightened: AD, AH, AI, AJ, AK, AN, BB) for which some further considerations are needed:

- All of these seven variables show relatively low values of factor loadings, between the 0.1512 of the variable BB (*Better decisions after training*) and the 0.4170 (in absolute value) of the variable AI (*Freedom in decision making*), meaning that none of the three factors clearly manages to represent those variables;
- All of these seven variables show relatively high values of uniqueness, between the 0.7007 of the variable AK (*Communication among departments*) and the 0.9600 of the variable BB (*Better decisions after training*), meaning that a considerable share of the variables' variance cannot be explained by factors
- Many of these seven variables show relatively low correlations with the remaining variables.

Therefore, after these three considerations, it was decided to drop the above-mentioned variables, and focus the analysis only on the rest of the variables.
Another factor analysis model was then estimated with the remaining set of variables. Here below (Figure 4.20) the table of factor loadings and uniqueness.

Rotated Factor loadings (pattern matrix) and unique variance					
Variable	Item	Factor1	Factor2	Factor3	Uniqueness
Z	Long-run strategy	0.4940	0.1915	0.0707	0.5561
AA	Communicate strategy	0.5237	0.0769	0.1128	0.5876
AB	Investments consistent with strategy	0.0657	0.0080	0.6761	0.4831
AC	Manufacturing consistent with strategy	0.0454	0.0084	0.7040	0.4605
AF	Functions interaction	0.0644	0.0022	0.6759	0.4888
AG	Functions cooperation	0.0129	-0.0724	0.7890	0.4174
AL	Team creation	0.6330	-0.0630	0.0548	0.6018
AM	Team for problem-solving	0.6778	-0.1883	-0.0172	0.6577
AO	Encouraging suggestions for improvement	0.6755	-0.0189	0.0164	0.5453
AP	Ideas exchanging	0.7240	-0.0330	0.0584	0.4527
AQ	Encouragement to work as a team	0.7759	-0.1525	0.0770	0.4461
AR	Importance of inter-functional relationships	-0.0172	0.1039	0.6510	0.5139
AS	Encouraging communication	0.0064	0.1070	0.7251	0.3815
AT	Multiple-tasks training	0.5513	0.2317	-0.0839	0.5627
AU	Cross-training	0.5070	0.1708	-0.0443	0.6472
AV	Reward people contribution	0.0005	0.7226	0.0807	0.4142
AW	Reward accomplished objectives	-0.0587	0.9113	0.0119	0.2162
AX	Incentives for reaching plant goals	-0.0506	0.9116	0.0108	0.2092
AY	Incentives for pursuing plant goals	0.0057	0.8885	-0.0085	0.2122
AZ	Importance of training	0.5169	0.2571	-0.0095	0.5256
BA	Continuous training	0.5050	0.3203	0.0064	0.4555

Figure 4.20: Rotated factor loadings and uniqueness for factor analysis of Purpose-Process-People (2)

Also in this case the highest weights for every variable have been enlightened (red). Having dropped the variables with ambiguous factor loadings, our factor analysis seems to become more well-defined. However, some rows are blue-enlightened also in this case. As a matter of facts, for variables Z, AA, AT, AU, AZ, and BA the values of the factor loadings are still relatively low, around 0.5, while for the other variables factor loadings are equal to 0.7, 0.8 or even 0.9. This fact means that also this variables are not adequately explained by factors. Moreover, if we keep in mind the item division that theory suggested (form Z to AG for Purpose, for AH to AS for Process, and from AT to BB for People, see Figure 4.12), these

variables do not fit it: they load on factors that are not the ones suggested by the theoretical model. Note that also variables AR and AS do not follow the theoretical item division that was hypothesized, but, unlike the previous variables, these two have quite high factor loadings (0.65 and 0.73) and therefore have not been enlightened. However, in this case it was decided not to immediately drop these variables, but to leave them and postpone the decision of whether to eliminate them or not to the Confirmatory Factor Analysis stage. If the goodness-of-fit indices will suggest a good model fit, there will be no necessity to drop them, otherwise, in the opposite case, we will eliminate those variables from the list.
To sum up, after this exploratory steps, we have arrived to a first variables division, that will be then tested in the CFA. The items are grouped in three categories (factors), each comprehending some variables, as follows:

- Factor 3 comprehending variables: AB, AC, AF, AG, AR, AS;
- Factor 1 comprehending variables: Z, AA, AL, AM, AO, AP, AQ, AT, AU, AZ, BA;
- Factor 2 comprehending variables: AV, AW, AX, AY.

4.5.2 Improvement

Passing to the variables describing Improvement and its meta-routines, we have to carry on a factor analysis on 13 items. As it was for the previous variables, the starting point is, also in this case, the variance-covariance matrix, thus making the first descriptive considerations. The matrix (fully displayed in Appendix A2) clearly shows that the highest correlation values (higher than 0.5) are those between the variables that belong to the same meta-routine (according to the qualitative division based on theory).
After this quick matrix inspection, it is time to estimate a factor analysis model, to understand first how many factors to retain, and then how variables distribute among these factors. For models with more than four factors the software warns that the estimation procedures are affected by Heywood Case, therefore a model fixing maximum four factors was estimated using the Maximum Likelihood criterion (output below).

```
Factor analysis/correlation                        Number of obs    =      266
    Method: maximum likelihood                     Retained factors =        4
    Rotation: (unrotated)                          Number of params =       46
                                                   Schwarz's BIC    =  278.014
    Log likelihood = -10.58652                     (Akaike's) AIC   =  113.173
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.77940	3.02527	0.6131	0.6131
Factor2	1.75413	0.68240	0.2250	0.8381
Factor3	1.07173	0.88099	0.1375	0.9755
Factor4	0.19074	.	0.0245	1.0000

```
LR test: independent vs. saturated:  chi2(78) = 1750.66 Prob>chi2 = 0.0000
LR test:   4 factors vs. saturated:  chi2(32) =   20.55 Prob>chi2 = 0.9411
```

As we can see, the factors whose eigenvalues are greater than 1 are three on four, thus suggesting that the optimum number of factors should be 3. Another model was then estimated, fixing 3 factors, and analogue conclusions can be drawn.

```
Factor analysis/correlation                        Number of obs    =      266
    Method: maximum likelihood                     Retained factors =        3
    Rotation: (unrotated)                          Number of params =       36
                                                   Schwarz's BIC    =  248.342
    Log likelihood =  -23.6683                     (Akaike's) AIC   =  119.337
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.89886	3.28050	0.6480	0.6480
Factor2	1.61836	0.57543	0.2141	0.8620
Factor3	1.04293	.	0.1380	1.0000

```
LR test: independent vs. saturated:  chi2(78) = 1750.66 Prob>chi2 = 0.0000
LR test:   3 factors vs. saturated:  chi2(42) =   46.06 Prob>chi2 = 0.3079
```

Not only the Kaiser criterion leads to this solution, but also the analysis of the scree plot as well. In Figure 4.21 it can be observed that from the fourth factor, the line of the scree plot tends to flatten over the horizontal axis.

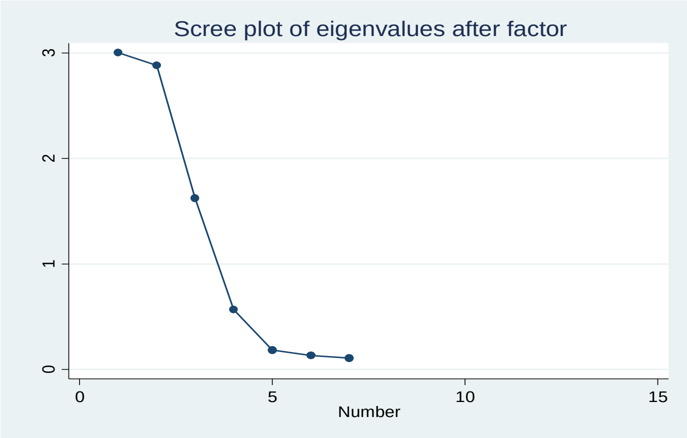


Figure 4.21: : Scree plot of eigenvalues for factor analysis of Improvement

After having determined the number of factors to be retained, we have to look at the factor loadings. Similarly to the previous case, factor loadings provided by the software need to be rotated. Also in this case it seems correct to assume a certain degree of correlation among factors, therefore the Promax oblique rotation has been adopted. In Figure 4.22 the table of factor loadings and uniqueness.

Rotated factor loadings (pattern matrix) and unique variances					
Variable	Item	Factor1	Factor2	Factor3	Uniqueness
A	Statistical techniques to reduce process variance	0.8699	-0.0179	0.0407	0.2224
B	Statistical quality control	0.9078	-0.0763	-0.0040	0.2382
C	Use of control charts	0.5481	0.1173	0.0796	0.5668
D	Statistical Process Control (SPC)	0.9413	0.0252	-0.0796	0.1596
E	provide personal leadership for quality products and quality improvement	-0.0987	0.8634	0.0554	0.2752
F	Creation and communication of a vision of quality improvement	0.0005	0.8278	-0.0130	0.3258
G	Management involved in quality improvement projects	0.0907	0.8014	-0.1088	0.3734
H	Department heads responsible for quality	0.0150	0.6187	0.0949	0.5344
I	Continued learning and improvement	0.1966	0.1706	0.3218	0.6765
J	Performance as a moving target	-0.0677	0.0752	0.6861	0.5131
K	Incremental improvement	0.0393	-0.0417	0.6013	0.6409
L	Continuous improvement	-0.0456	0.0477	0.7108	0.4872
M	Dynamic approach	0.0293	-0.0729	0.7802	0.4264

Figure 4.22: : Rotated factor loadings and uniqueness for factor analysis of Improvement (1)

The analysis of the rotated factor loadings indicates that the distribution of the variables among the three factors is quite satisfactory. Every variable loads strongly on just one factor (values enlightened in red), and the gap between the highest factor loading and the two others is wide. The distribution of the variable is also in accordance with the division suggested by theory. The only exception is the variable I (*Continued learning and improvement*), in correspondence of which there is: low factor loading (0.3218), high uniqueness (0.6765) and very low correlation with the other variables of the group (all smaller than 0.41). For this reason variable I was eliminated from the list, and another factor model was estimated (Figure 4.23).

Rotated factor loadings (pattern matrix) and unique variances

Variable	Item	Factor1	Factor2	Factor3	Uniqueness
A	Statistical techniques to reduce process variance	0.8631	-0.0107	0.0545	0.2187
B	Statistical quality control	0.8991	-0.0691	0.0098	0.2351
C	Use of control charts	0.5470	0.1242	0.0790	0.5695
D	Statistical Process Control (SPC)	0.9290	0.0329	-0.0692	0.1636
E	provide personal leadership for quality products and quality improvement	-0.0883	0.8534	0.0652	0.2758
F	Creation and communication of a vision of quality improvement	0.0068	0.8186	0.0038	0.3216
G	Management involved in quality improvement projects	0.0946	0.7907	-0.0973	0.3759
H	Department heads responsible for quality	0.0232	0.6145	0.0990	0.5353
J	Performance as a moving target	-0.0503	0.0853	0.6765	0.5083
K	Incremental improvement	0.0545	-0.0273	0.5822	0.6464
L	Continuous improvement	-0.0282	0.0573	0.7040	0.4785
M	Dynamic approach	0.0506	-0.0529	0.7523	0.4375

Figure 4.23: : Rotated factor loadings and uniqueness for factor analysis of Improvement (2)

Having dropped variable I, our factor analysis looks very well-defined. There are no low loadings and the distribution of variables fits the theoretical structure that had been hypothesized. The items are grouped in three categories (factors), each comprehending some variables, as follows:

- Factor 1 comprehending variables: A, B, C, D;

- ❖ Factor 2 comprehending variables: E, F, G, H;
- ❖ Factor 3 comprehending variables: J, K, L, M.

4.6 Confirmatory factor analysis

Through the exploratory factor analysis it has been possible to "explore" every potential structure of the factor model, without fixing any parameter and letting free every variable to load on every factor. We have, in this way, arrived to a model specification that seems to fit our data. However, the goodness of this model needs to be tested through a series of indices and other calculations that represent the core of the Confirmatory Factor Analysis (CFA). In the CFA, in fact, the researcher already has a well-defined model, comprehending both free and fixed parameters, and wants to "confirm" its validity.

4.6.1 Purpose, Process, People

For the first part of the variables, regarding the elements of CI infrastructure, the exploratory factor analysis led to a model made of 21 variables and 3 factors, divided as shown in Figure 4.24.

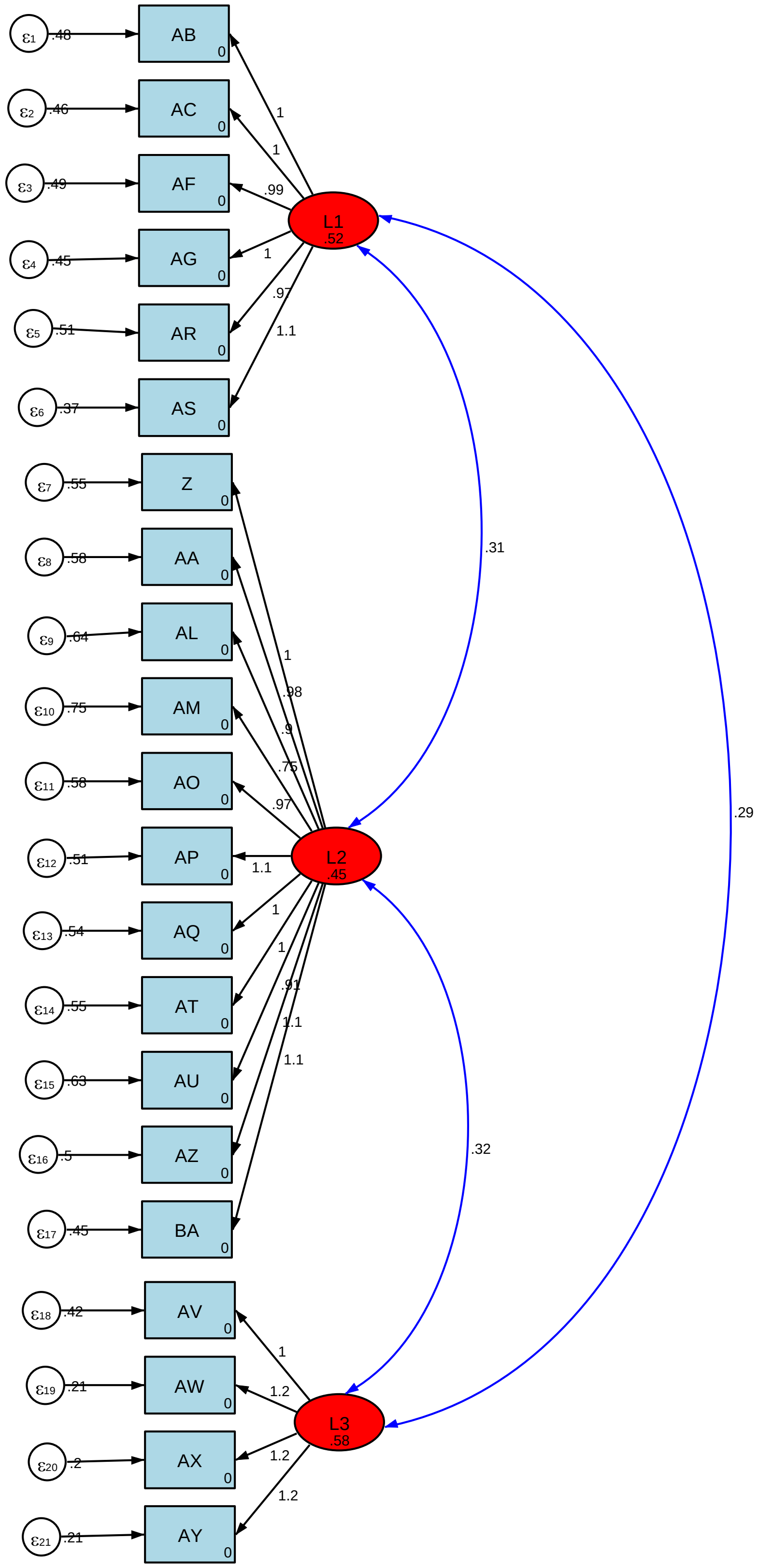


Figure 4.24: Confirmatory factor model for categories Purpose, Process, People (1)

The table of the overall goodness-of-fit indices provided by the software is:

Fit statistics		description	value	Close-fit value
Likelihood ratio	χ^2_ms(186)	model vs. satured	558,113	NA
	p>χ^2		0,000	
	χ^2_bs(210)	baseline vs. satured	3316,367	NA
	p>χ^2		0,000	
	Normed χ^2	χ^2/df	3,001	<3
Population error	RMSEA	Root mean squared error of approximation	0,087	<0.08
Baseline comparison	CFI	Comparative fit index	0,880	>0.9
	TLI	Tucker-Lewis index	0,865	~1
Size of residuals	SRMR	Standardized root mean squared residual	0,060	<0.1
	CD	Coefficient of determination	0,998	>0.8

Figure 4.25: Goodness-of-fit indices for Purpose-Process-People CFA model (1)

In the figure above there is an outlook of all the most important fit indices, along with the close-fit values in the last column. What these indices suggest is that model fit is not excellent at all. A RMSEA value of 0.087 is beyond the borderline of acceptable levels; generally a value of RMSEA between 0.05 and 0.08 indicates acceptable model fit, and values higher than 0.08 indicate bad model fit. Here this index is higher than 0.08 and this fact scores a point for model misspecification. The Comparative fit index is also under the close-fit value (and the TLI as well), while the Normed χ^2 shows a borderline situation. For the rest of the indices the situation seems acceptable. However, it is sure that model fit can be improved. Therefore, it was decided to go one step backward and drop those six variables (Z, AA, AT, AU, AZ, BA) that in the EFA were not so satisfactory, since their factor loadings were relatively low and were not in accordance with the model structure suggested by theory . Having cancelled these variables from the factor model, another one was estimated, whose structure is displayed in Figure 4.26 and goodness-of-fit indices in Figure 4.27.

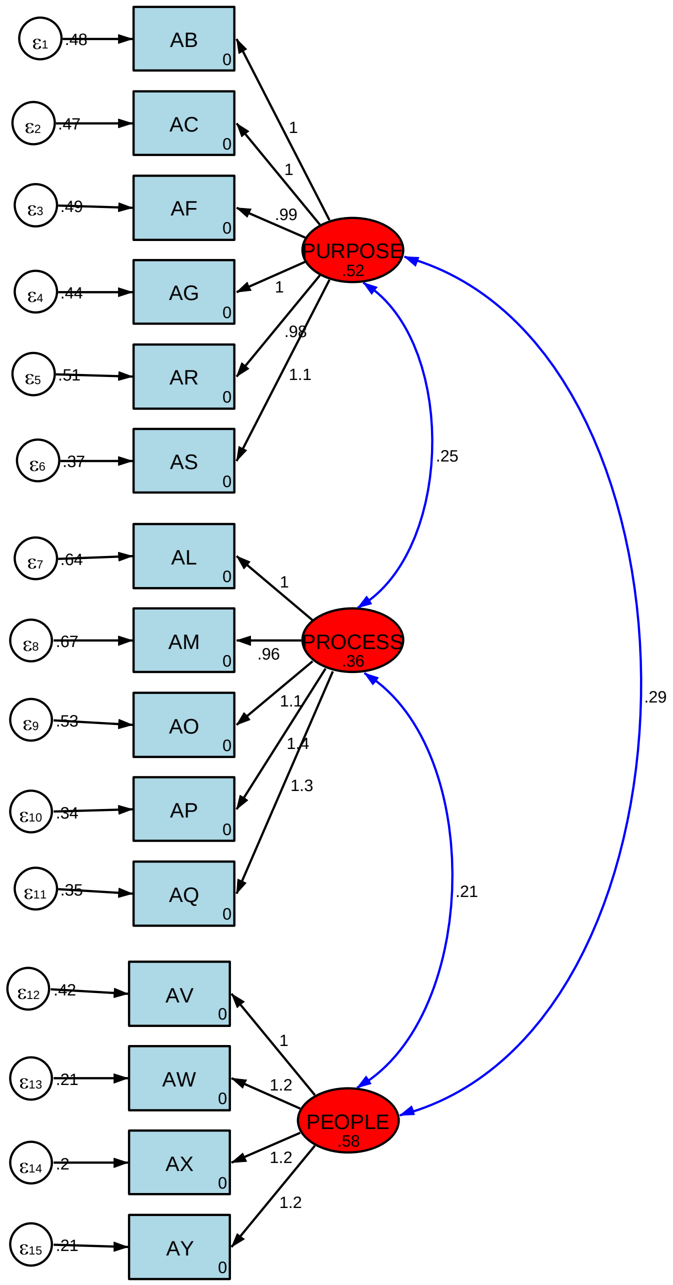


Figure 4.26: Confirmatory factor model for categories Purpose, Process, People (2)

Fit statistics		description	value	Close-fit value
Likelihood ratio				
	χ^2_ms(87)	model vs. satured	174,159	NA
	p>χ^2		0,000	
	χ^2_bs(105)	baseline vs. satured	2248,515	NA
	p>χ^2		0,000	
	Normed χ^2	χ^2/df	2,002	<3
Population error				
	RMSEA	Root mean squared error of approximation	0.061	<0.08
Baseline comparison				
	CFI	Comparative fit index	0.959	>0.9
	TLI	Tucker-Lewis index	0.951	~1
Size of residuals				
	SRMR	Standardized root mean squared residual	0.044	<0.1
	CD	Coefficient of determination	0.998	>0.8

Figure 4.27: Goodness-of-fit indices for Purpose-Process-People CFA model (2)

It looks evident at first glance that, after this slight model modification, the model fit has massively improved. First of all, the RMSEA dropped from an unacceptable 0.087 to a good 0.061; moreover, the Normed χ^2 has significantly improved (from 3.001 to 2.002), as well as the CFI and TLI indices.

In order to be sure that the measurement model that has just been tested is the definitive one, we'd better look at other measures that allow some further considerations. First, for every equation of the measurement model, coefficients were analysed along with their relative standard errors, thus testing their significance through a Wald test. Moreover, the R-squared, for testing equation-level fit, was calculated (Figure 4.28).

Parameters’ significance and R-squared					
Variables	**Coefficient**	**Standard error**	**z**	**p-value**	**R-squared**
Measurement					
AB ← Purpose	1		(constrained)		0.518
AC← Purpose	1.015	0.089	11.39	0.000	0.533
AF← Purpose	0.992	0.092	10.77	0.000	0.509
AG← Purpose	1.036	0.092	11..31	0.000	0.555
AR← Purpose	0.975	0.092	10.60	0.000	0.492
AS← Purpose	1.099	0.093	11.88	0.000	0.626
AL← Process	1		(constrained)		0.359
AM← Process	0.957	0.122	7.85	0.000	0.329
AO← Process	1.147	0.133	8.64	0.000	0.472
AP← Process	1.352	0.144	9.40	0.000	0.656
AQ← Process	1.347	0.143	9.44	0.000	0.651
AV← People	1		(constrained)		0.578
AW← People	1.168	0.075	15.66	0.000	0.789
AX← People	1.174	0.077	15.35	0.000	0.798
AY← People	1.166	0.077	15.09	0.000	0.786
Covariances					
Purpose - Process	0.248	0.043	5.73	0.000	
Purpose - People	0.287	0.047	6.09	0.000	
Process - People	0.206	0.040	5.14	0.000	
overall					0.998

Figure 4.28: Parameters’ significance and R-squared for equations for Purpose-Process-People CFA model

The outcome of the test reveals that every manifest variable has a statistically significant effect on their respective factor, since all the z-values (resulting from the division of estimates by their respective standard error) are greater than the 5% quantile of a standardized Normal (1.64) and, therefore, led to the rejection of the null hypothesis (parameter equal to zero). Note that for variables AB, AL and AV the test was not calculated; that happens because these values of the parameters defining the relations between these manifest variables and their respective latent ones have been fixed to 1, thus providing a metrical parameterization to latent variables that are, by nature, unobserved and therefore with no measurement unit. Since this constrain is in place, no Wald test can be carried out. The covariances between the three latent variables Purpose, Process and People are all significant as well.

For what regards the R-squared, it can be observed that variables AL and AM have a relatively low value (0.359 and 0.329, respectively); however, it was decided not to drop these two variables.

Finally, it is time to check the modification indices (MI) suggested by our software. Ignoring modification indices regarding covariances among manifest variables, the only additional path that is suggested is the one between the variable AG and the latent factor People. For this relation there is a reduction of the χ^2 statistic of 5.09 (remember that MI are significant at 5% level for values greater than 3.84). However, since in our model it was assumed that each item loads on only one of the three categories of CI infrastructure, it was decided not to keep into account of the additional path suggested by MI.

Modification indices

	MI	df	P>MI	EPC	Standard EPC
Measurement					
AG <-					
PEOPLE	5.090	1	0.02	-.1711151	-.1301389

At this point, both the exploratory and the confirmatory factor analysis for the elements of CI infrastructure have come to the end. The final model comprehends a set of 15 variables grouped into 3 categories, each referring to the Purpose-Process-People scheme. In particular:

- Under the category <u>Purpose</u> there are the following variables:
  - AB: *Investments consistent with strategy*
  - AC: *Manufacturing consistent with strategy*
  - AF: *Functions interaction*
  - AG: *Functions cooperation*
  - AR: *Importance of inter-functional relationships*
  - AS: *Encouraging communication;*
- Under the category <u>Process</u> there are the following variables:

- AL: *Team creation*
- AM: *Team for problem solving*
- AO: *Encouraging suggestions for improvement*
- AP: *Ideas exchanging*
- AQ: *Encouragement to work as a team;*

➢ Under the category People there are the following variables:

- AV: *Reward people contribution*
- AW: *Reward for accomplished objectives*
- AX: *Incentives for reaching plant goals*
- AY: *Incentives for pursuing plant goals.*

4.6.2 Improvement

Passing to the second set of variables (Improvement), the exploratory factory analysis led to a model made of 12 variables grouped into 3 factors, as shown in Figure 4.29.

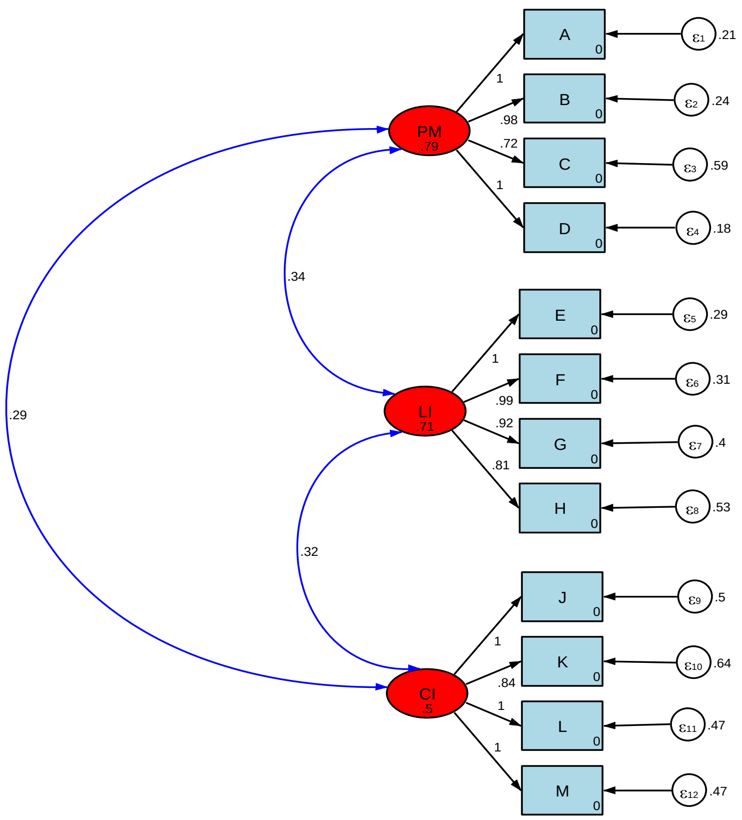


Figure 4.29: Confirmatory factor model for Improvement

Nonetheless, for this part of the analysis, there is one further step to take. As a matter of facts, what the economic theory suggests (Peng (2007)) is that these three meta-routines that have been identified, are all consequences of another superior element, and therefore can be adequately explained by one single factor, that is Improvement itself. The result, then, is a <u>second-level factor model</u>, where *Process Management* (PM), *Leadership Involvement* (LI), and *Continuous Improvement* (CI) are the first-level factors, while *Improvement* is the second-level factor, that explains them. The new model is displayed in Figure 4.30, and its respective goodness-of-fit indices in Figure 4.31.

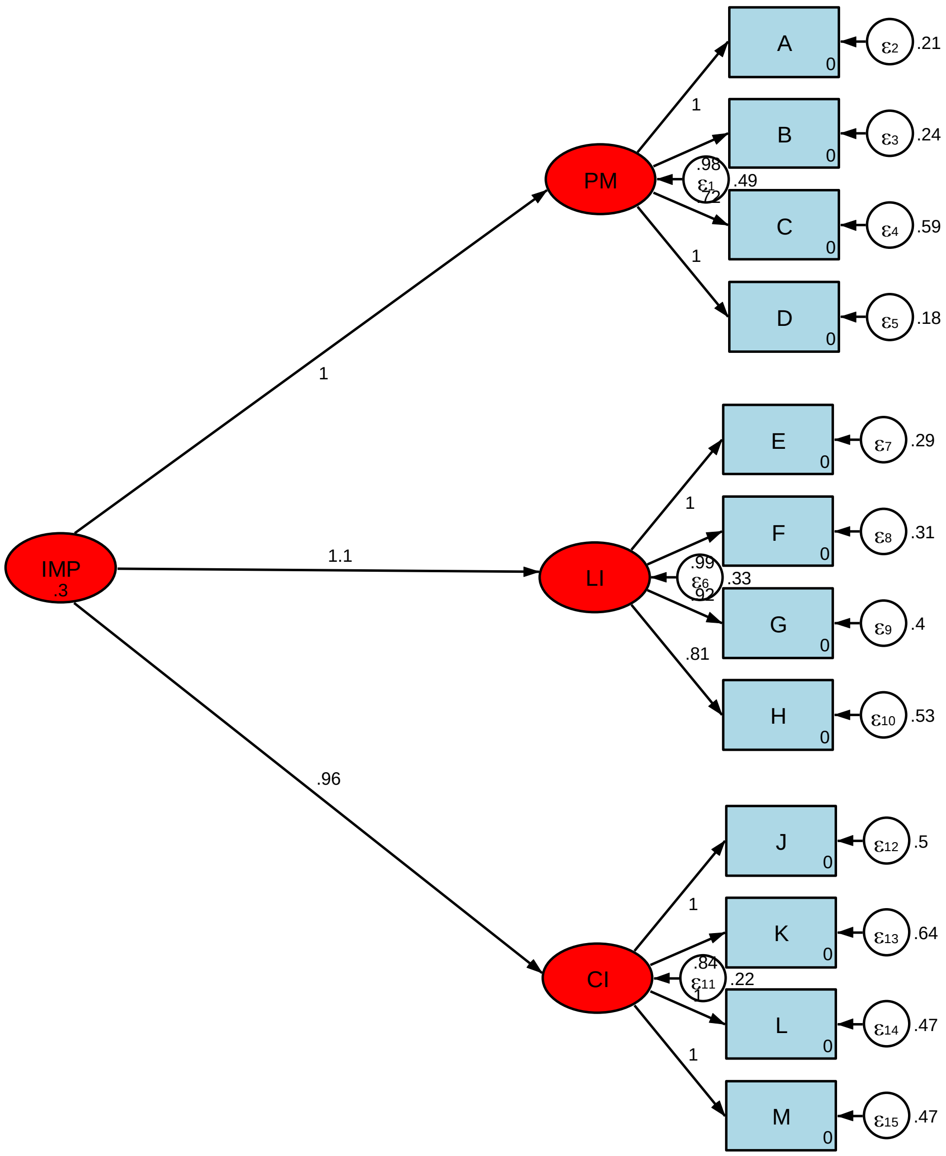


Figure 4.30: Second-level confirmatory factor model for Improvement

Fit statistics		description	Value	Close-fit value
Likelihood ratio				
	χ^2_ms(51)	model vs. satured	75,112	NA
	p>χ^2		0,141	
	χ^2_bs(66)	baseline vs. satured	1684,903	NA
	p>χ^2		0,000	
	Normed χ^2	χ^2/df	1,473	<3
Population error				
	RMSEA	Root mean squared error of approximation	0,042	<0.08
Baseline comparison				
	CFI	Comparative fit index	0,985	>0.9
	TLI	Tucker-Lewis index	0,981	~1
Size of residuals				
	SRMR	Standardized root mean squared residual	0,043	<0.1
	CD	Coefficient of determination	0,750	>0.8

Figure 4.31: Goodness-of-fit indices for second-level confirmatory factor model for Improvement

The above-listed statistics suggest that the second-level factor model adequately fits data. The most significant element in this, is the low value of RMSEA (0,042) below the borderline value of 0,05, meaning a close fit for our model. The SRMR is also very low (0,043) and the normed χ^2 is just 1,473; in general, apart for thee Coefficient of Determination, all the fit statistics have values that mean very good model fit.

Afterwards, every equation was considered and the Wald test and R-squared were calculated, in order to test respectively parameters' significance and model fit at equation level (Figure 4.32). The equations explaining the second-level factor *Improvement* through the first-level factors *Process Management, Leadership Involvement, Continuous Improvement,* were also considered, since they are real equations of a linear regression, and not only covariances (as the latent variables in the previous case). Tests confirm significance of both the manifest variables and the first-level factors for every equation (for variables A, E, J, PM it was not calculated because of the latent variables' parameterization); the R-squared is almost always high, apart in a couple of cases (variables C, K, Process Management) where it is below 0.42.

Parameters' significance and R-squared					
Variables	**Coefficient**	**Standard error**	**z**	**p-value**	**R-squared**
Measurement					
A ←PM	1		(constrained)		0.787
B←PM	0.982	0.050	19.69	0.000	0.759
C←PM	0.723	0.061	11.78	0.000	0.411
D←PM	1.022	0.049	20.91	0.000	0.821
E←LI	1		(constrained)		0.707
F←LI	0.988	0.066	15.02	0.000	0.690
G←LI	0.919	0.067	13.73	0.000	0.598
H←LI	0.812	0.068	11.90	0.000	0.466
J←CI	1		(constrained)		0.501
K←CI	0.843	0.101	8.36	0.000	0.355
L←CI	1.027	0.104	9.85	0.000	0.528
M←CI	1.031	0.106	9.71	0.000	0.532
Structural					
PM←IMP	1		(constrained)		0.380
LI←IMP	1.124	0.190	5.92	0.000	0.535
CI←IMP	0.960	0.168	5.70	0.000	0.551
overall					0.750

Figure 4.32: Parameters' significance and R-squared for equations for second-level factor model for Improvement

Finally, the modification indices were considered. Our software calculates that there are several additional paths that could be taken in consideration, in correspondence of which the modification indices are significant (greater than 3.84). However, these paths were not applied, not to alter the structure of the model and the hypothesis made at the beginning.

	MI	df	P>MI	EPC	Standard EPC
Structural					
PM <-					
C	9.585	1	0.00	-.4115822	-.4639183
E	6.126	1	0.01	-.2865996	-.3230431
G	4.623	1	0.03	.1925837	.2170723
LI <-					
B	4.068	1	0.04	-.2266836	-.2696378
C	4.767	1	0.03	.1385102	.1647564
CI <-					
D	4.768	1	0.03	-.2776874	-.392491
Measurement					
A <-					
C	4.184	1	0.04	-.0985996	-.0985996
B <-					
E	4.481	1	0.03	-.0809529	-.0809529
G	3.852	1	0.05	-.0737289	-.0737289
LI	4.533	1	0.03	-.1099292	-.0924171
C <-					
A	4.184	1	0.04	-.2727607	-.2727607
E	6.537	1	0.01	.1349281	.1349281
G	6.482	1	0.01	.1324017	.1324017
H	8.402	1	0.00	.1481861	.1481861
M	6.328	1	0.01	.1299886	.1299886
LI	8.376	1	0.00	.2049433	.1722952
CI	6.017	1	0.01	.2190299	.1549637
IMP	9.585	1	0.00	.4970209	.2719521
D <-					
G	4.956	1	0.03	.0785992	.0785992
L	6.458	1	0.01	-.08899	-.08899
E <-					
A	3.978	1	0.05	-.0915201	-.0915201
B	5.347	1	0.02	-.1054227	-.1054227
D	4.421	1	0.04	-.097257	-.097257
PM	5.113	1	0.02	-.1283608	-.1138801
G <-					
D	7.805	1	0.01	.1371351	.1371351
M	4.534	1	0.03	-.1031118	-.1031118
M <-					
G	4.268	1	0.04	-.117402	-.117402

Chapter 5

The complete structural model

Having concluded the entire factor analysis both for the elements of CI infrastructure and for Improvement and its meta-routines, the complete structural model is ready to be explained in this chapter.

First of all, a global measurement model will be built, in order to assess the validity of the overall model; then, discriminant and divergent analysis will take place. In the discriminant analysis some nested models will be tested; these nested models are created merging constructs that were initially separated, and they will be subsequently analysed in order to determine which of the models (the complete one or one of the nested) better fits empirical data. In the convergent analysis the focus is represented by those variables that are already grouped under the same construct, and it will be tested whether data reasonably justify these different variables to be grouped together.

Afterwards, it will be possible to assess which is the best model, and the structural coefficients will be analysed, in order to evaluate any significant relation between the exogenous and endogenous latent variables. What theory suggests is that there should be a significant positive relations between the adoption of techniques under one of the *Purpose, Process, People* categories and the Improvement. The discussion of these results, however, will take place in the final paragraph of this work.

5.1 The measurement model

In order to build a complete model that displays the relations between Improvement and its infrastructure, we need to link the two parts of the model that, until now, have always been kept divided. However, it is not time yet to create a structural model that describes relations between them in the form of linear regression equations. Before doing this, it is necessary to analyse the complete measurement model, as it were still part of the Confirmatory Factor Analysis. In particular, the structure of the model should be nothing but the mix of the two confirmatory factor models for Improvement and its infrastructure, where the relations between them is in the form of covariances values, i.e., in the path-diagram representation, of double-arrowed curved lines.

The complete measurement model is displayed in Figure 5.1 and the table of its goodness-of-fit indices in Figure 5.2.

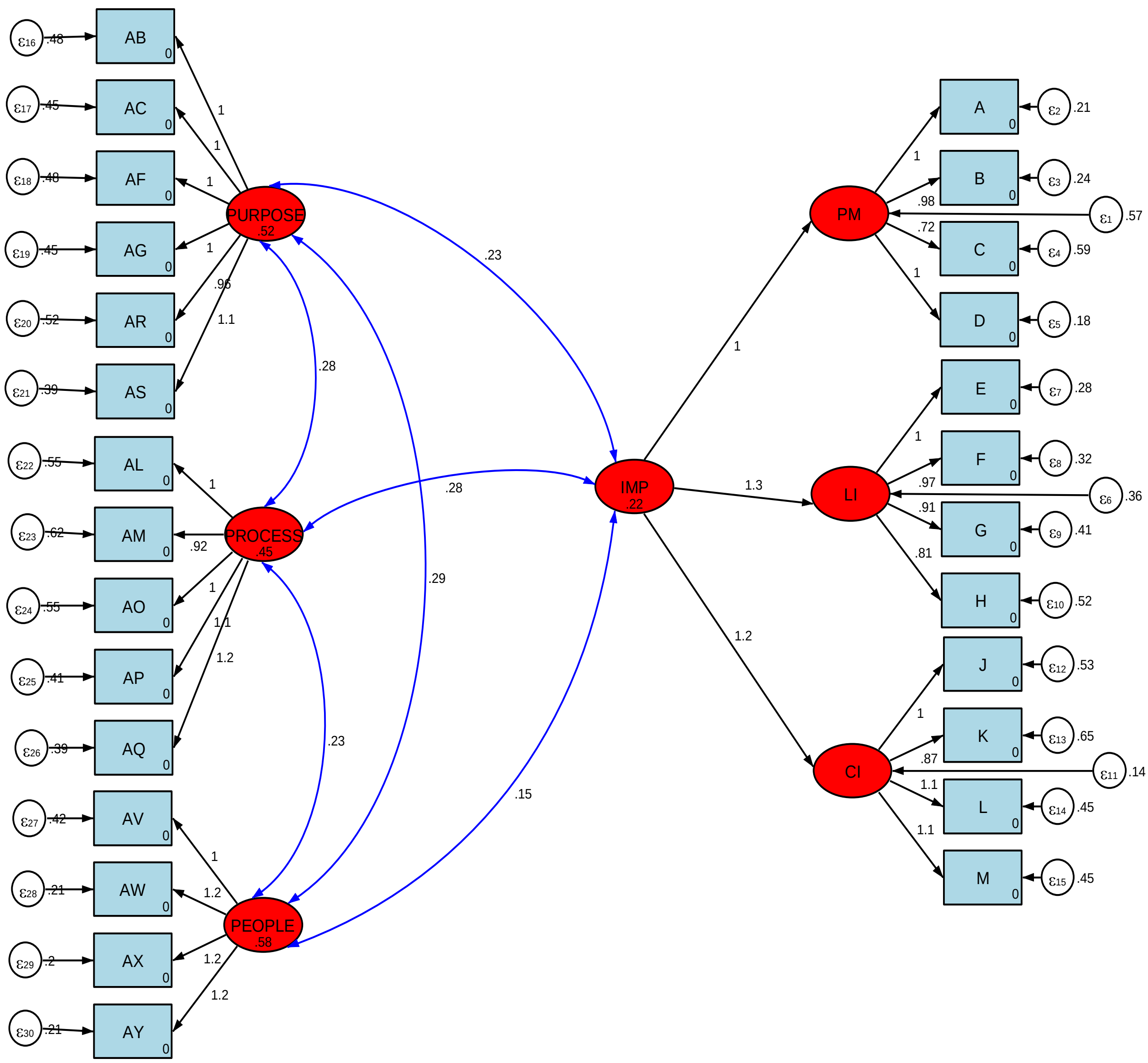


Figure 5.1: Complete measurement model (and estimates)

Fit statistics		description	value	Close-fit value
Likelihood ratio				
	χ^2_ms(315)	model vs. satured	538.926	NA
	p>χ^2		0,000	
	χ^2_bs(351)	baseline vs. satured	4403.736	NA
	p>χ^2		0,000	
	Normed χ^2	χ^2/df	1.711	<3
Population error				
	RMSEA	Root mean squared error of approximation	0.052	<0.08
Baseline comparison				
	CFI	Comparative fit index	0.945	>0.9
	TLI	Tucker-Lewis index	0.938	~1
Size of residuals				
	SRMR	Standardized root mean squared residual	0.062	<0.1
	CD	Coefficient of determination	0.999	>0.8

Figure 5.2: Goodness-of-fit indices for the measurement model

The report of the goodness-of-fit indices suggests that model fit is good, since every index is within the range of close-fit values. In particular, the RMSEA is almost equal to 0.05 (0.052) and the Normed χ^2 is far smaller than 3 (1.711).

Having verified the overall model fit, we can have a look at the variables' coefficients and their significance. In Figure 5.3 every regression coefficient is shown, along with their relative standard error and p-value (for significance test); in the last column there are also values of the R-squared. For the equations defining the latent variables through their respective manifest ones, tests on parameters confirm significance of all the variables at 1% level; the first level-latent factors (PM, LI, CI) that measure the second-level factor (Improvement) are significant as well. As regards the core of the measurement model, i.e. all the possible covariances between *Purpose*, *Process*, *People* and Improvement, tests confirm significance of each covariance drawn in the diagram.

Parameters' significance and R-squared					
Variables	**Coefficient**	**Standard error**	**Z**	**p-value**	**R-squared**
<u>Measurement</u>					
A ←PM	1		(constrained)		0.787
B←PM	0.982	0.050	19.70	0.000	0.760
C←PM	0.722	0.061	11.7 7	0.000	0.411
D←PM	1.021	0.049	20.90	0.000	0.821
E←LI	1		(constrained)		0.718
F←LI	0.971	0.064	15.16	0.000	0.677
G←LI	0.907	0.066	13.83	0.000	0.591
H←LI	0.814	0.067	12.12	0.000	0.476
J←CI	1		(constrained)		0.470
K←CI	0.866	0.103	8.43	0.000	0.352
L←CI	1.078	0.106	10.13	0.000	0.546
M←CI	1.078	0.108	10.02	0.000	0.546
AB ← Purpose	1		(constrained)		0.522
AC← Purpose	1.024	0.088	11.58	0.000	0.547
AF← Purpose	1.001	0.092	10.94	0.000	0.522
AG← Purpose	1.029	0.091	11..34	0.000	0.552
AR← Purpose	0.961	0.091	10.56	0.000	0.482
AS← Purpose	1.081	0.091	11.84	0.000	0.609
AL← Process	1		(constrained)		0.450
AM← Process	0.921	0.102	9.02	0.000	0.382
AO← Process	0.998	0.110	9.10	0.000	0.448
AP← Process	1.147	0.116	9.91	0.000	0.591
AQ← Process	1.165	0.116	10.06	0.000	0.610
AV← People	1		(constrained)		0.578
AW← People	1.168	0.075	15.64	0.000	0.788
AX← People	1.175	0.077	15.34	0.000	0.798
AY← People	1.167	0.077	15.08	0.000	0.787
<u>Structural</u>					
PM←IMP	1		(constrained)		0.274
LI←IMP	1.291	0.191	6.75	0.000	0.502
CI←IMP	1.229	0.187	6.57	0.000	0.694
<u>Covariances</u>					
Purpose - Process	0.281	0.047	6.00	0.000	
Purpose - People	0.288	0.047	6.09	0.000	
Process - People	0.231	0.043	5.31	0.000	
IMP - Purpose	0.228	0.042	5.40	0.000	
IMP - Process	0.276	0.048	5.71	0.000	
IMP - People	0.152	0.034	4.45	0.000	
overall					0.999

Figure 5.3: Parameters' significance and R-squared for the complete measurement model

5.2 Discriminant validity

Discriminant validity is the first half of a more general procedure that goes under the name of "construct validity". Construct validity can be viewed as an overarching term to assess the validity of the measurement procedure (e.g., a questionnaire) that is used to measure a given construct (Campbell & Fiske, 1959). The two main subcategories that compose the technique of construct validity, and that work together to strengthen their efficacy, are discriminant validity and convergent validity. In order to make immediately a clear distinction between convergent and discriminant validity it can be assessed that, while convergent validity refers to the degree to which two measures that theoretically should be related are, in fact, related, discriminant validity tests whether measures that are supposed to be unrelated are, in fact, unrelated. From a practical point of view: in the convergent validity we are interested in the extent to which certain fit-measures converge (i.e., we want to see a strong relationship between scores on the same construct), while in the discriminant validity we are interested in the extent to which these measures diverge (i.e., we want to see little or no relationship between scores from the two constructs).

Whereas convergent validity will be more relevantly discussed in the next paragraph (1.3), in this part we will focus on discriminant validity, and we will exploit it to draw significant conclusions on our measurement model.

With regard to our specific model, the measures that we want to "discriminate" are represented by the latent variables of the structural model, in particular by the three elements of Continuous Improvement infrastructure (*Purpose, Process, People*) and Improvement itself. Note that the first-level factors (Process Management, Leadership Involvement and Continuous Improvement) that explain the second-level factor Improvement have not been considered in the discriminant analysis, because they are part of the measurement model and not of the structural model (that will be examined in the end of the chapter). In order to properly affirm that these separated constructs represent, in fact, different concepts, we need to create a series of alternative models, where, by hypothesis, some of these constructs are merged together. The alternative models that are, in this way, created are nothing but constrained (and therefore nested) models of the complete one; in particular, the operation of merging two latent variables into a unique single one, is equal to constraining the correlation between these two variables equal to 1. In fact, when the correlation between two variables is 1, it means that the variation of one of the variables exactly corresponds to the same variation of the other one, and therefore they can be considered as a unique variable. It was then decided to consider the four variables that form the structural model, group these latent variables two by two, and analyse the outcome compared to the complete model.

Now, some issues need to be clarified. Since all the alternative models that are going to be tested are nested models of the general one (illustrated in Figure 5.1), they have a number of free parameters that is intrinsically lower (since some constraints are in place) . In statistics, whenever one or more parameters are detracted, the explanation power of the model automatically decreases. So, if on one hand a large number of variables seems desirable, on the other hand a model overloaded with parameters is not parsimonious at all, and does not satisfy the main requirement of a statistical model, i.e., its ability to provide a simplified representation of reality. We have then model fit as opposed to model parsimoniousness. Therefore, when some distance-measures, such as the χ^2-statistic are analysed, in order to evaluate model fit, each of the nested model will have, for sure, a higher value (i.e. worse model fit) than the one of the complete model. Nevertheless, if the model simplification that is gained through this parameters reduction justifies the (small) rise in the χ^2-statistic, then the nested model will be preferred over the general one. What makes all the difference in choosing a nested model over a more general one is, therefore, the difference of the χ^2-statistic between the two models. If this quantity is not statistically significant, then the reduction in the model fit is justified by the simplification gained and the nested model will be chosen; on the contrary, if the difference of the χ^2-statistic is statistically significant, the complete model will be chosen over the nested one.

Grouping two by two a series of 4 different constructs, implies considering in total 6 different cases, each of them composed by a different mixing combination of the four variables. Keeping in mind the complete model of Figure 5.1, we have graphically listed all of the different combinations. In Figures 5.4 (*a* and *b*) the same complete measurement model is displayed, but in every figure, within a dotted oval black line, the constructs that have been merged are enlightened.

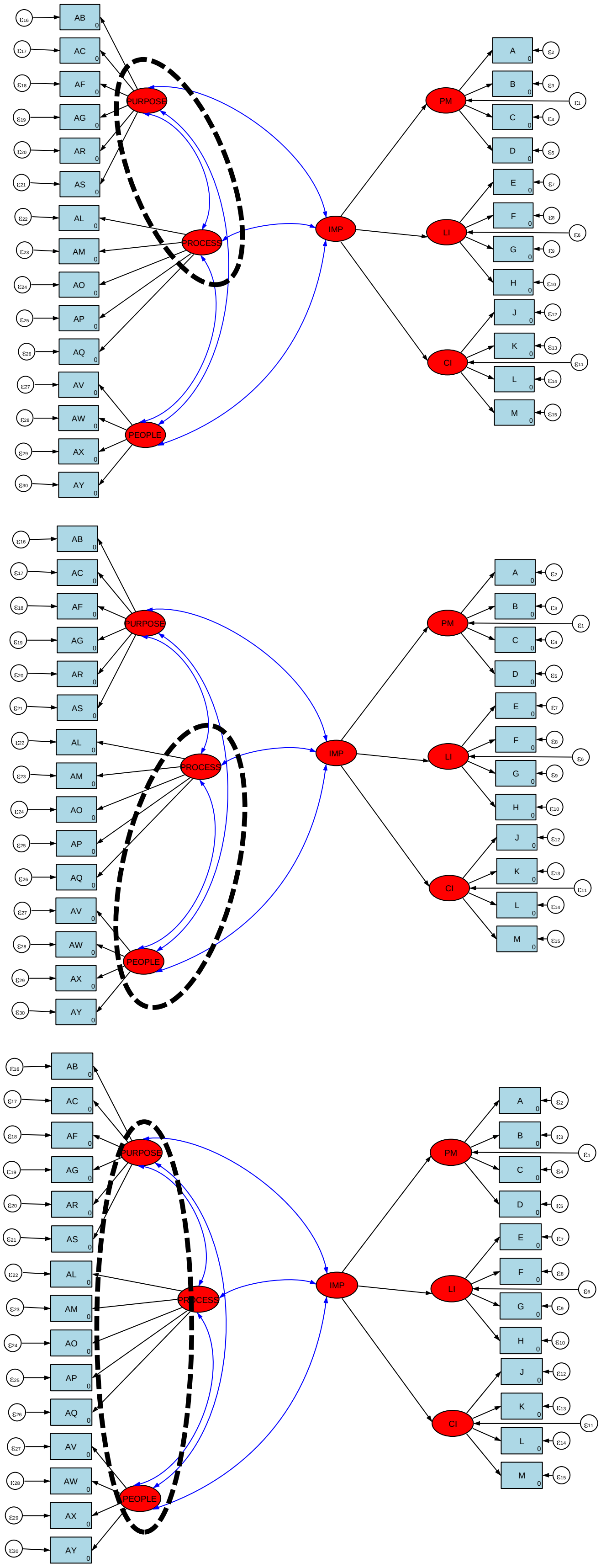


Figure 5.4(a): Different mixing-combinations for the variables of the structural model (1)

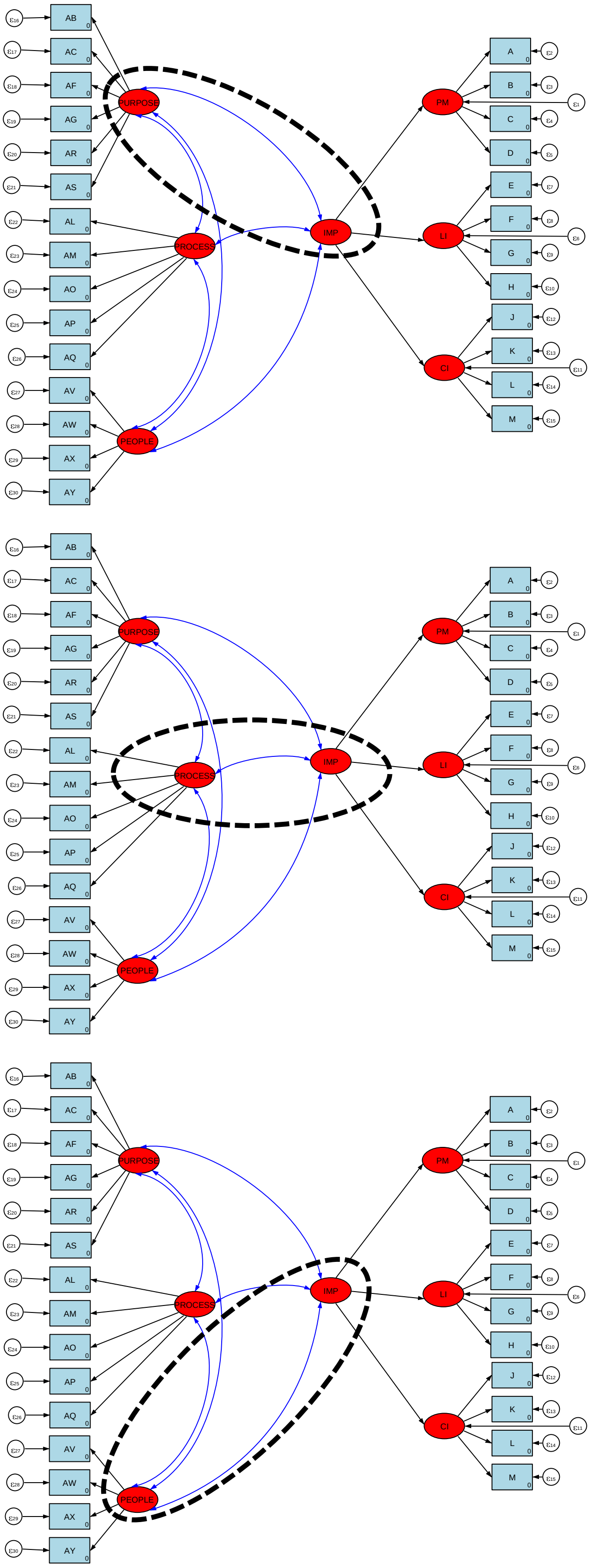


Figure 5.4(b): Different mixing-combination for the variables of the structural model (2)

For each of the 6 different cases the χ^2-statistics have been calculated (Figure 5.5).

χ^2-statistic	PURPOSE	PROCESS	PEOPLE	IMPROVEMENT
PURPOSE				
PROCESS	811.843			
PEOPLE	1025.862	980.916		
IMPROVEMENT	643.458	554.406	769.576	

Figure 5.5: χ^2-statistics for the nested models

Afterwards, knowing the value of the χ^2-statistic of the complete model (538.926), the differences of the χ^2-statistics ($\Delta\chi^2$) have been easily calculated as well.

$\Delta\chi^2$-statistic	PURPOSE	PROCESS	PEOPLE	IMPROVEMENT
PURPOSE				
PROCESS	272.917			
PEOPLE	486.936	441.99		
IMPROVEMENT	104.532	15.48	230.65	

Figure 5.6: $\Delta\chi^2$-statistics for the nested models compared to the complete one

In order to assess whether the values of the $\Delta\chi^2$ are statistically significant or not, we need to compare them to the χ^2 distribution; but with how many degrees of freedom? Now, each of the constrained models has 318 degrees of freedom, exactly 3 more than the number of degrees of freedom of the complete model (315). When analysing the $\Delta\chi^2$, the number of degrees of freedom to refer to is exactly equal to the difference of the number of the degrees of freedom of the models, in this case 3. Checking the tabulated χ^2 distribution with 3 df (the third row of the table here below), we can see that it is significant at 0.05 level for values greater than 7.81, and at 0.01 for values greater than 11.34. Therefore, to draw some conclusions, we can say that all the values of the $\Delta\chi^2$ shown in Table 5.6 are statistically significant and, therefore, when constraining the complete model, there is a significant reduction in the model fit, not enough justified by the simplification gained with a simpler model. So, in the end, the complete model is better than all of the nested ones that have been considered.

Note that, for almost all of the nested models, the values of the $\Delta\chi^2$ are very high (higher than 100), meaning a strongly significant raise in the χ^2 when adding the constraints, and a clear preference for the complete model over one of the nested. However, in one case, i.e. when considering the model where *Process* and Improvement have been merged together, the value of the $\Delta\chi^2$ is much lower (15.48). Although it still remains significant at 0.01 level (it is still greater than 11.34), the situation is not as well-defined as in the previous cases, since this value is massively lower than the others $\Delta\chi^2$. This fact will be the input of some interesting theoretical points that will be examined in the conclusion paragraph.

Degrees of Freedom	Probability of a larger value of x ²								
	0.99	**0.95**	**0.90**	**0.75**	**0.50**	**0.25**	**0.10**	**0.05**	**0.01**
1	0.000	0.004	0.016	0.102	0.455	1.32	2.71	3.84	6.63
2	0.020	0.103	0.211	0.575	1.386	2.77	4.61	5.99	9.21
3	0.115	0.352	0.584	1.212	2.366	4.11	6.25	7.81	11.34

The $\Delta\chi^2$ analysis leads to the conclusion that the complete model is preferable over the nested ones, and, for this reason, that the four different, separated constructs that compose the structural part of the model (*Purpose*, *Process*, *People*, and Improvement) should remain, effectively, separated.

In order to strengthen this position, there are some further elements that can be considered. The AIC (Akaike Information Criterion), for example, is another interesting tool used to compare groups of nested models. The concept under this measure is that, when two nested models are compared, the one with the lowest value of AIC is preferable over the other. In Figure 5.7 the AIC values are displayed for every combination of models. The value of the AIC for the complete model is 16642.823 and, as we can see, it is lower than any of the values of the AIC for the nested models. Therefore, not only the $\Delta\chi^2$, but also the AIC goes in the same direction, suggesting that the complete model is preferable. As well as $\Delta\chi^2$, then, also in this case, for the nested model where the variables *Process* and Improvement are mixed, the difference is not as evident as in the other cases, since the value of the AIC is just slightly higher than the one of the complete model (16652.303).

AIC	PURPOSE	PROCESS	PEOPLE	IMPROVEMENT
PURPOSE				
PROCESS	16909.740			
PEOPLE	17123.760	17078.813		
IMPROVEMENT	16741.356	16652.303	16867.473	

Figure 5.7: AIC values for the nested models

Finally, the RMSEA of the different combination of models was calculated (Figure 5.8) and compared to the RMSEA of the complete measurement model (0.052); also in this case analogue conclusions can be drawn.

$RMSEA$	PURPOSE	PROCESS	PEOPLE	IMPROVEMENT
PURPOSE				
PROCESS	0.076			
PEOPLE	0.091	0.089		
IMPROVEMENT	0.062	0.053	0.073	

Figure 5.8: RMSEA values for the nested models

5.3 Convergent validity

In the discriminant validity it has been demonstrated that those variables that were supposed to be separated (as indicators of different constructs) have to be, in fact, separated. Now, in order to complete the analysis of construct validity, we need to carry on a convergent analysis.

Unlike discriminant validity, convergent validity refers to the degree to which two measures of constructs that theoretically should be related to each other, are in fact observed to be related to each other, i.e. a certain level of convergence and correspondence between them should be spotted. The extent to which convergent validity has been demonstrated is established by the strength of the relationship between the scores that are

obtained from the two different elements that have been used to collect data about a certain construct. The idea is that if these scores converge, despite the fact that we used two different measurement elements, we must be measuring the same construct. In this case, convergent analysis allows assessing that those separated elements actually correspond with one another.
Having specified these basic notions, we have to understand how convergent validity can be applied to our model. As it has just been written, the focus of convergent validity is represented by those variables that, although separated from a technical point of view, are supposed to measure the same construct. In our model, those variables that are grouped under larger constructs are the manifest variables that measure the three elements of CI infrastructure (*Purpose, Process, People*) and the three meta-routines of Improvement (Process Management, Leadership Involvement, Continuous Improvement). These manifest variables are simply the expressions of the answers given to the items of the questionnaire. Therefore, convergent validity for our model has to be tested taking into account the manifest variables (or items) that are grouped under the same latent variable (or construct). What we expect to find, is that the values of some indices that measure the degree of connection between these variables confirm that they are effectively close-related, and that are generally different measures for the same unique single general construct.
At this point, the only further tool needed is a series of indices that could provide a quantitative expression of the degree of association for the items. Statistical theory in this field suggests three main indices useful to test convergent validity:

- <u>Cronbach's alpha</u>: it is the most widely used measure of internal consistency; it is a function of the number of items and the average interitem covariance. It varies from 0 to 1, and values of α equal or higher than 0.7 are generally considered evidences of good internal consistency. It is calculated as:

$$\alpha = \frac{N \bar{r}}{1 + (N - 1)\, \bar{r}}$$

Where *N* is the number of items and $\bar{r}$ is the average interitem covariance.

- AVE (Average Variance Extracted): it is a statistic that states how much variance captured by the latent variable in a structural equation model is shared among other variables. In different terms, AVE is a measure of the error-free variance of a set of items. Values greater than 0.5 are desirable. It is:

$$AVE = \frac{\sum\left(\lambda_i{}^2\right) Var(X)}{\sum\left(\lambda_i{}^2\right) Var(X) + \sum Var(\varepsilon_i)}$$

Where λ_i is the loading of x_i (item *i*) on X, $Var(X)$ denotes variance of the latent variable, and ε_i is the measurement error of x_i.

- Composite reliability (*ρ*): it is another, least frequently adopted measure of composite reliability, often used in substitution of Cronbach's alpha. Its close-fit values are those greater than 0.6. Its formula is:

$$\rho = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum Var(\varepsilon_i)}$$

The calculation of Average Variance Extracted, as well as Composite Reliability, requires a structural equation model to already exist, since it needs the loadings of the indicators for the latent variable for which it is to be calculated. The structural equation model to refer to is, in these cases, the measurement model, i.e. the model that has been used in the confirmatory factor analysis stage (Paragraph 4.6).

Hence, these three indicators have been calculated, first for the three groups of items belonging to the CI infrastructure (*Purpose*, *Process*, *People*) (Figure 5.9) and then for the three meta-routines of Improvement (Process Management, Leadership Involvement, Continuous Improvement) (Figure 5.10).

	Cronbach's alpha [critical value: 0.7]	AVE [critical value: 0.5]	Composite Reliability [critical value: 0.6]
PURPOSE	0.8746	0.5387	0.9311
PROCESS	0.8259	0.4934	0.9300
PEOPLE	0.9164	0.7377	0.9509

Figure 5.9: Convergent validity for items of the categories *Purpose, Process, People*

	Cronbach's alpha [critical value: 0.7]	AVE [critical value: 0.5]	Composite Reliability [critical value: 0.6]
Process Management	0.8932	0.6946	0.9191
Leadership Involvement	0.8611	0.6151	0.8999
Continuous Improvement	0.7836	0.4791	0.8796

Figure 5.10: Convergent validity for items of the categories Process Management, Leadership Involvement, Continuous Improvement

For the first three latent variables, convergent analysis points out that the items belonging to the same group are consistent. Each of the three indices is over its critical value for every group; in particular, the values of Composite Reliability seem remarkably high. The only exception is represented by the AVE calculated for the items under the construct *Process*: AVE is equal to 0.4934, however, it is very close to 0.5.

For the three meta-routines of Improvement the situation looks pretty analogue: indices above the close-fit values, very high composite reliability values. There is an exception also in this case, represented by the AVE for the latent variable Continuous Improvement, that is 0.4791 and therefore below the critical value. Nevertheless, as well as for the three previous groups, also for these ones it can be assessed that the overall internal consistency for the different groups is very satisfactory.

5.4 The structural model

The measurement model that was discussed in the first paragraph of this chapter, and whose structure is fully displayed in the diagram in Figure 5.1, is aimed at providing a global representation of the two measurement sub-models in a single graph where, on the left there is the factor model regarding the elements of Improvement infrastructure, and on the right the second-level factor model regarding Improvement and its routines. The connection between these two parts is represented by the covariances that link the latent variables *Purpose, Process, People* to the second-order latent variable Improvement. The above-mentioned measurement model is the best one of them all, and this can be assessed thanks to the results obtained in the discriminant and convergent analysis. In the former, in fact, it was demonstrated the consistency of constructs that had been kept separated, while in the latter it was demonstrated the consistency of constructs that had been grouped together.

Once the measurement model is verified, the next step consists of estimating a real structural model for the latent variables of the structural part, creating precise regression equations that define the relations between the latent variables. In particular, these equations will explain the relations between *Purpose, Process, People,* and Improvement, since this part is the structural "core" of the model and is the one for which a certain type of causality pattern is assumed.

Linking the statistical notions to the econometrical theory the model is based on, we can say that what is going be created, is a hypothetical model where the operational activities (or, more properly, bundles of activities) grouped under the categories *Purpose, Process, People* "cause" improvement, stimulate it, creates the conditions in which Improvement is more easily developed and spread. The statistical outcome of this model will help to understand if this is true, that translating into statistical language, if these causality relations are significant, if they are statistically justified by the data at our disposal.

Therefore, the purpose of this final phase of this work can be summarized in a set of three hypothesis to be statistically tested:

- The bundle of activities named *Purpose* has a statistically significant effect on Improvement (H_1);

- The bundle of activities named *Process* has a statistically significant effect on Improvement (H_2);
- The bundle of activities named *People* has a statistically significant effect on Improvement (H_3).

The graphical structure of the hypothesis testing is displayed in Figure 5.11 here below.

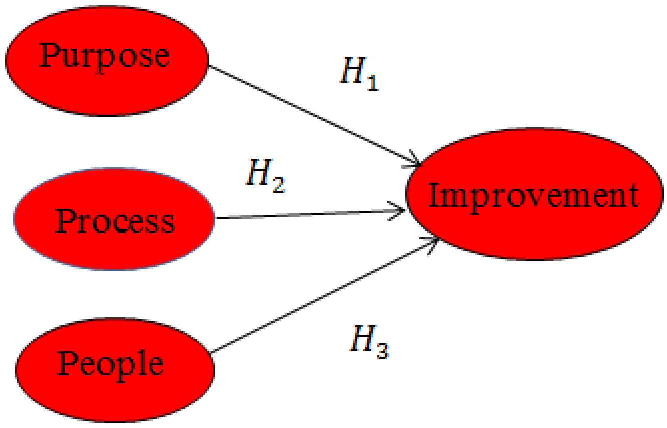


Figure 5.11: Hypothesis testing on the structural model

Before starting with the estimation procedure, it is correct to provide a clear identification of the model, in particular through the definition of the four matrices that define the structural part of a SEM model: **B**, **Γ**, **Φ** and **Ψ**.
The matrix *beta* is a square matrix 4x4, with a number of rows and columns equal to the number of endogenous latent variables η. On the main diagonal there are just 0, because these values correspond with the regression coefficient of every variable with itself. The parameter β_{14} has been fixed to 1, because of the need for a metrical parameterization for the latent variable Improvement. All the remaining parameters are 0, except for β_{24} and β_{34}, that define the relations of respectively Leadership Involvement and Continuous Improvement, with Improvement; therefore, these two parameters are the only unconstrained values of **B**.

$$B = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & \beta_{24} \\ 0 & 0 & 0 & \beta_{34} \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The matrix *gamma* represents the regression of the latent exogenous variables on the latent endogenous variables. Its dimension are 4x3, i.e. number of rows equal to the number of latent endogenous variables and number of columns equal to the number of exogenous variables.

$$\boldsymbol{\Gamma} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \gamma_{41} & \gamma_{42} & \gamma_{43} \end{bmatrix}$$

All values are constrained to 0, except γ_{41}, γ_{42} and γ_{43} that define the relations of the three latent exogenous variables *Purpose, Process and People*, with the second-level endogenous latent variable Improvement.

The other two matrices of the structural model are in the form of variance-covariance matrices. The first is the matrix *phi*, comprehending covariances of the latent exogenous variables (ξ); it, therefore, expresses the variances-covariances of *Purpose, Process* and *People* and its dimension is 3x3.

$$\boldsymbol{\Phi} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} \end{bmatrix}$$

None of the elements of this matrix are constrained, since in our model it was assumed that the covariances between *Purpose, Process and People* are free parameters and that have to be estimated. However, since it is a variance-covariance matrix, $\boldsymbol{\Phi}$ is symmetric and values below the main diagonal are symmetrical to those over the main diagonal (φ_{21}=φ_{12}, φ_{31}=φ_{13}, φ_{32}=φ_{23}). Note that, as a squared symmetric matrix, we could have written $\boldsymbol{\Phi}$ in the form of a triangular matrix, ignoring the upper triangle of the matrix.

Finally, the matrix *psi* shows covariances between error terms ζ. Its dimension is 4x4, because 4 is the number of endogenous variables η, that, obviously, coincides with the number of the error terms ζ. As well as matrix $\boldsymbol{\Phi}$, matrix $\boldsymbol{\Psi}$ is a squared symmetric matrix too. In our model no covariances between endogenous latent variables are defined, so Ψ has 0 in every place of the matrix out of the main diagonal, while in the main diagonal there are values of the variances.

$$\boldsymbol{\Psi} = \begin{bmatrix} \psi_{11} & 0 & 0 & 0 \\ 0 & \psi_{22} & 0 & 0 \\ 0 & 0 & \psi_{33} & 0 \\ 0 & 0 & 0 & \psi_{44} \end{bmatrix}.$$

Now that the complete structural model has been totally defined, both theoretically and statistically, we can proceed estimating the model. The model diagram is fully displayed in Figure 5.12.

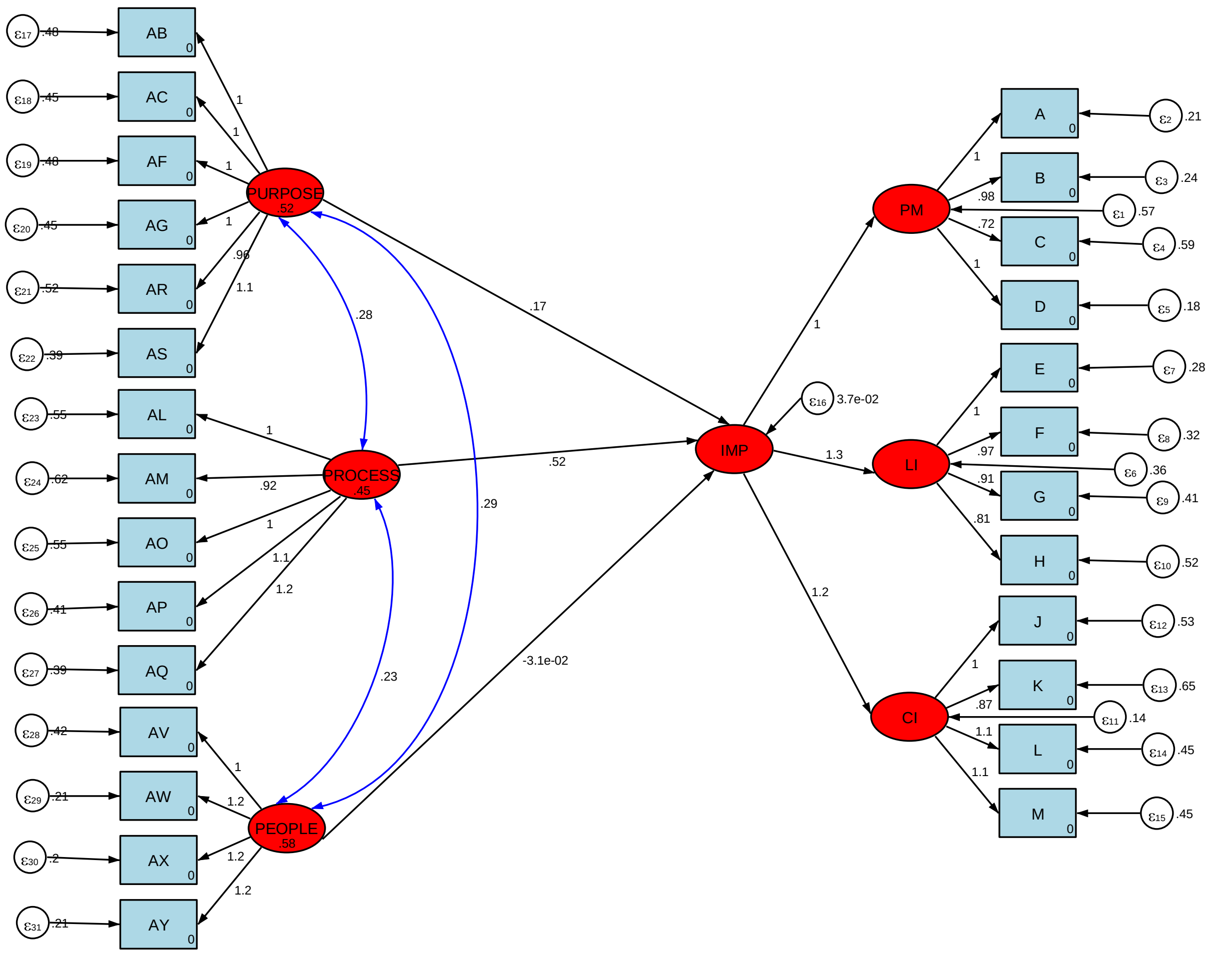


Figure 5.12: Complete structural model (and estimates)

Fit statistics		description	value	Close-fit value
Likelihood ratio	χ^2_ms(316)	model vs. satured	538.926	NA
	p>χ^2		0,000	
	χ^2_bs(351)	baseline vs. satured	4403.736	NA
	p>χ^2		0,000	
	Normed χ^2	χ^2/df	1.705	<3
Population error	RMSEA	Root mean squared error of approximation	0.051	<0.08
Baseline comparison	CFI	Comparative fit index	0.945	>0.9
	TLI	Tucker-Lewis index	0.939	~1
Size of residuals	SRMR	Standardized root mean squared residual	0.062	<0.1
	CD	Coefficient of determination	0.998	>0.8

Figure 5.13: Goodness-of-fit indices for the complete structural model

In Figure 5.13 we can see the table that summarizes the main goodness-of-fit indices for the structural model. If compared with the analogue table that had been calculated for the measurement model (Figure 5.2), we can see that these two outcomes are practically identical. Therefore, as well as in the measurement model, also in the structural model there is a very good model fit: every index is in the “close-fit area”, in particular Normed χ^2 is far less than 3 and RMSEA is just slightly higher than 0.05.

Afterwards, we can go into the real essence of this study: the analysis of the regression coefficients of the structural model; in particular of the coefficients that define the relations between the elements of CI infrastructure *Purpose, Process and People*, and Improvement, thus making it possible to test the above-mentioned set of hypothesis (Figure 5.11) and to discover whether there is a significant causal effect between these constructs. These coefficients are shown in the matrix **Γ**, because it regards the regression coefficients of the latent exogenous variables on the latent endogenous variables. In Figure 5.14 there is the complete list of the coefficients of the model, along with Standard Error, Z value, p-value (for testing parameters’ significance) and R-squared.

Parameters’ significance and R-squared					
Variables	**Coefficient**	**Standard error**	**Z**	**p-value**	**R-squared**
Measurement					
A ←PM	1		(constrained)		0.787
B←PM	0.982	0.049	19.97	0.000	0.760
C←PM	0.722	0.062	11.60	0.000	0.411
D←PM	1.021	0.049	20.75	0.000	0.821
E←LI	1		(constrained)		0.718
F←LI	0.971	0.064	15.12	0.000	0.677
G←LI	0.907	0.067	13.57	0.000	0.591
H←LI	0.814	0.067	12.13	0.000	0.476
J←CI	1		(constrained)		0.470
K←CI	0.866	0.094	9.19	0.000	0.352
L←CI	1.078	0.093	11.59	0.000	0.546
M←CI	1.078	0.096	11.28	0.000	0.546
AB ← Purpose	1		(constrained)		0.522
AC← Purpose	1.024	0.088	11.58	0.000	0.547
AF← Purpose	1.001	0.092	10.94	0.000	0.522
AG← Purpose	1.029	0.091	11..34	0.000	0.552
AR← Purpose	0.961	0.091	10.56	0.000	0.482
AS← Purpose	1.081	0.091	11.84	0.000	0.609
AL← Process	1		(constrained)		0.450
AM← Process	0.921	0.102	9.02	0.000	0.382
AO← Process	0.998	0.110	9.10	0.000	0.448
AP← Process	1.147	0.116	9.91	0.000	0.591
AQ← Process	1.165	0.116	10.06	0.000	0.610
AV← People	1		(constrained)		0.578
AW← People	1.168	0.075	15.64	0.000	0.788
AX← People	1.175	0.077	15.34	0.000	0.798
AY← People	1.167	0.077	15.08	0.000	0.787
Structural					
PM←IMP	1		(constrained)		0.274
LI←IMP	1.291	0.143	9.02	0.000	0.502
CI←IMP	1.229	-	-	-	0.694
IMP← Purpose	0.173	0.056	3.09	0.002	
IMP← Process	0.523	0.071	7.39	0.000	
IMP← People	-0.031	0.042	-0.76	0.450	
Covariances					
Purpose - Process	0.281	0.047	6.00	0.000	
Purpose - People	0.288	0.047	6.09	0.000	
Process - People	0.231	0.043	5.31	0.000	
overall					0.998

Figure 5.14: Parameters’ significance and R-squared for the complete structural model (**Γ** coefficients enlightened)

In order to provide a clearer representation of the statistical model outcome, the four matrices of the structural part are displayed here below.

$$\mathrm{B} = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1.291 \\ 0 & 0 & 0 & 1.229 \\ 0 & 0 & 0 & 0 \end{bmatrix} \qquad \mathbf{\Gamma} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.173 & 0.523 & -0.031 \end{bmatrix}$$

$$\mathbf{\Phi} = \begin{bmatrix} 0.522 & 0.281 & 0.288 \\ 0.281 & 0.450 & 0.231 \\ 0.288 & 0.231 & 0.578 \end{bmatrix} \qquad \mathbf{\Psi} = \begin{bmatrix} 0.571 & 0 & 0 & 0 \\ 0 & 0.358 & 0 & 0 \\ 0 & 0 & 0.144 & 0 \\ 0 & 0 & 0 & 0.037 \end{bmatrix}$$

Now that all the necessary elements have been collected, we are able to properly evaluate the three hypothesis made about the effects of CI infrastructure on Improvement. Let's see them one by one:

- **$\mathbf{H_1}$**: The bundle of activities named *Purpose* has a statistically significant effect on Improvement

The coefficient γ_{41} (that represents the causal relation of *Purpose* on Improvement) has a value of 0.173, with a standard error of 0.056, thus providing a p-value of 3.09. According to the standardized normal distribution critical values, 3.09 corresponds to a significance level of 0.002 (0.2%) , that is enough to confirm the significant effect of the parameter. The outcomes of the model, then, suggest that the bundle of activities named *Purpose*, characterized by the alignment between operational and strategic goals, has a statistically significant impact on Improvement and, in turn, on its meta-routines.

- **$\mathbf{H_2}$**: The bundle of activities named *Process* has a statistically significant effect on Improvement

For γ_{42} there is a coefficient value of 0.523 with a standard error of 0.071, that gives a p-value of 7.39, that is highly significant in the case of a standardized normal distribution. This fact denotes that not only has the bundle named *Process* a statistically significant effect on Improvement, but also has a remarkably high regression coefficient (0.523), meaning a strong causal effect; this strong relationship between *Process* and Improvement represents an important clue that will be the input of some important observations drawn in the conclusions' paragraph.

- **H_3**: The bundle of activities named *People* has a statistically significant effect on Improvement

The situation of γ_{43} looks different from the previous two cases. The coefficient value is low and, most important, denotes a negative effect (-0.031); with a p-value of -0.76 (-0.031/0.042) it is NOT significant at all. Therefore, the hypothesis H_3 is rejected by our structural model. As for the previous two hypotheses, also in this case the theoretical interpretations and implications of this result (in particular the important role that plays the element of reward in the *People* factor) are postponed to the conclusive part of this work.

5.4.1 Indirect effects

All the coefficients of the structural model that have been shown in Figure 5.14 are all direct effects of one variable on another one. By direct effect we mean the variation of one variable caused by the variation of one unit of another variable, keeping all the others constant. Nevertheless, the causal effect of one variable on another one might be intermediated by a third variable that works as a link between the two variables and creates an indirect effect. In other words, there is an indirect effect between two variables X_1 and X_2 when the variation of X_1 causes the variation of a third variable X_3 that, in turn, causes the variation of the variable X_2. In this way, the relationship between X_1 and X_2 is mediated by the variable X_3. The apparently inexistent causal relation (in the output of the structural model) between X_1 and X_2 actually exists, in the form of a "causal chain" between variables, as shown in the graphical representation below.

$$X_1 \longrightarrow X_3 \longrightarrow X_2$$

Linking this notion to our structural model, we can see that the three variables describing the Improvement infrastructure (*Purpose*, *Process*, *People*) have a causal effect on the latent variable Improvement that, in turn, has a causal effect on the three routine bundles of

Improvement (Process Management, Leadership Involvement, Continuous Improvement). This is an example of the above-mentioned indirect effects between variables:

Purpose/Process/People ⟶ Improvement ⟶ PM/LI/CI

The model that was previously estimated, however, didn't take into account of these indirect effects, and considered the total effect among variables only as direct effect[12]. For this reason, it was decided to estimate the indirect effects that the variables *Purpose, Process* and *People* might have on the three meta-routines of Improvement, and to test their significance, thus providing a more complete description of the causal relations in place in the model. The outcome of the estimates of the indirect effects is displayed in Figure 5.15.

INDIRECT EFFECTS				
	Coefficient	**Standard error**	**Z**	**p-value**
Process Management				
Purpose	0,1731	0,0561	3,09	0,002
Process	0,5226	0,0708	7,39	0,000
People	-0,0314	0,0415	-0,76	0,450
Leadership Involvement				
Purpose	0,2235	0,0788	2,84	0,005
Process	0,6748	0,0908	7,43	0,000
People	-0,0405	0,0536	-0,76	0,450
Continuous Improvement				
Purpose	0,2128	0,0689	3,09	0,002
Process	0,6423	0,0870	7,39	0,000
People	-0,0386	0,0510	-0,76	0,450

Figure 5.15: Indirect effects of *Purpose/Process/People* on the three meta-routines of Improvement

What the estimates of the indirect effect suggest is that the constructs *Purpose* and *Process* have a significant indirect effect on PM, LI and CI (as we can see from the column of the p-values) and this effects is positive. It seems, then, that *Purpose* and *Process* has a causal relation both on Process Management, Leadership Involvement and Continuous Improvement, and that this relation is intermediated by the variable Improvement. These

[12] Total effect = Direct effect + Indirect effects

results are in accordance with the lean theory, according to which an increase in those activities regarding *Purpose* and *Process* actually fosters better performances in the areas of better process management, involvement of employees and *kaizen* activities. On the other side, the construct *People* shows something different. The p-values clearly suggest that the indirect effects of this category on any of the three meat-routines of Improvement are not statistically significant at any level. Note that, when analysing the structural model's coefficients, the category *People* had a non-significant direct effect on Improvement; therefore, we can assess that the overall model analysis, comprehending both direct and indirect effects, clearly shows that this construct has a non-significant total effect in the structural model.

At this point the final structural model has been fully studied, and the statistical model analysis comes to its end. In order to sum up the conclusions and provide a theoretical interpretation of the results that have been obtained, the conclusions paragraph was dedicated in the following part.

Conclusions

The *High Performance Manufacturing* project represents an outstanding source of potential information for those who are interested in lean management and want to understand the dynamics and mechanisms that make this new revolutionary management approach so famous and aspired. Generally speaking, if on one side the benefits of the adoption of all the techniques that lean management promotes are well-known, the quantitative and causal relations that are in place are not frequently studied. The purpose of this work is, indeed, to understand the causal relations between bundles of lean activities and their impact on Improvement within a firm; and this is made thanks to the big amount of data that the HPM makes available. In particular, following the framework proposed by Anand (2009), the bundles of lean activities have been grouped into the three elements that compose the infrastructure of Continuous Improvement: *Purpose, Process, People*. Afterwards, it was tested whether variations in the adoption of techniques belonging to one of these three groups caused a significant variation in the level of those elements through which Improvement is measured.

In order to provide a clear and general view of all the aspects embodied in the categories *Purpose, Process*, and *People,* a wide range of specific techniques and lean notions should have been considered. In this work, however, the three constructs regarding the Improvement infrastructure, as well as the three meta-routines into which Improvement has been decomposed, are latent variables each of them measured by a set of items extracted by the HPM questionnaires. This fact implies that a relatively small amount of items has been used to measure constructs that actually should comprehend more elements. This represented a sort of deficit for our model that had to be overcome. Since, as just mentioned, it would have been very laborious to keep into account all the items that could represent the three categories, it was decided to adopt a strict item selection process, and to consider a smaller set of items (related one another) that considered only some specific aspects of *Purpose, Process* or *People*, instead of considering them in their entirety. In simpler words, the notions of *Purpose/Process/People* are too general to be measured by a small amount of items and, for this reason, it was decided to adopt an item selection procedure that focused on specific single aspects of these categories. The reader might dispute that this choice could be a bit too drastic, and he/she probably would be right; nevertheless, an empirical analysis where some specific aspects of more general constructs are causally related to Improvement and its routines is not be undervalued, since also in this case some important considerations can be drawn.

Starting from the category *Purpose,* the final outcome of the model shows a statistically significant positive effect on Improvement. If we go backward and check the items that compose this category, we can see that *Purpose* is strongly related to the notion of alignment between operational and strategic goals, and is also related to the pursuit of an inter-functional cooperation and communication within the firm. Therefore these two aspects (operational and strategic goals alignment and inter-functional cooperation and communication) are those on which the category *Purpose* (as intended in this work) focuses on. The positive causal effect between *Purpose* and Improvement can be interpreted in the sense that, in order to gain some relevant benefits in the Continuous Improvement activities, an adequate strategy must be well-defined and understood. A business strategy correctly defined and properly communicated to all the employers represents the fundament for a sustainable CI initiative and a powerful impulse for a steady pursuit of better ways of doing things; without all this, in fact, it would be hard to head all the improvement efforts in the right direction, and these efforts would risk to be dispersed or weakened as time passes. In other words, the strategy works as a guiding light for the lean production system and all the techniques that it embodies, and it’s absolutely important that all of them are consistent with it. Moreover, the different functions of the firm have not to be considered as single isolated units, but have to work synergistically to achieve the strategic goals (as well as the operational goals that, as just said, have to be consistent with them). To make this possible, a constant interaction, communication and cooperation between the functional areas should be encouraged: they have to work together, share goals, help each other to solve problems, and so on, and not be treated as isolated boxes. After all, it is only though a constant knowledge exchanging that more supplementary knowledge emerges and leads to better performances.

For what regards the construct *Process* and its causal relation with Improvement, our structural model showed a significant positive relation also in this case; moreover, the coefficient between *Process* and Improvement was also particularly high (0.523). But what does the category *Process* focus on in our work? Again, looking backward at the items that form this category we can note that the attention is stressed on the notion of team work: team creation, encouragement to work as a team to solve problems, and so on. Besides, the notion of ideas exchanging and suggestions for improvement is present as well. Everyone who has at least a general knowledge about lean production system should know how utterly important "team" is in this management philosophy. Lean management strongly believes in the power of people as a source knowledge, useful for improving productivity and eliminating waste; and this is possible if people work not in separated, isolated departments, but if they merge together in teams. In this sense, the strict relationship between the bundle *Process* and Improvement is highly justified: working in teams, in fact, enhance commitment and responsibility in every production process, stimulates the creation of new and alternative solutions to problems, it is a source of job enrichment; and all this represents a powerful impulse for Continuous Improvement, because more efficient processes with no waste intrinsically mean better performances and, therefore, improvement. In addition to this, the fact that people have the possibility to express their ideas and suggestions for improvement is also very important. Remember that lean philosophy points out that the most important source for improvement in production processes is the workers located in the production plants; they have the processes in front of them all day and their suggestions for improvement activities within the firm must not absolutely be undervalued. Therefore, *Process* (as intended here) is a fundamental causal element of Improvement, because it represents some of the most important notions in lean system. A proof of this fact is the results of the discriminant analysis carried out in the paragraph 5.2: the $\Delta\chi^2$ statistic showed a relatively low value (although still significant) when mixing the categories *Process* and Improvement, compared to the other nested models. This occurred because these two constructs are so strongly related each other that they almost tend to coincide, and therefore relatively little differences are spotted between models where *Process* and Improvement are separated or merged together.

The last category to be analysed is *People*. As well as in the previous cases, we have first to look carefully at the items that have been used for this category. The four items that have been grouped (see Figure 4.12) are all related to the utilization of systems of reward and incentives for pursuing and accomplishing plant objectives; therefore, the aspect of *People* we focused on is reward and compensation. And what does our statistical model say? The reader for sure remembers that the coefficient defining the causal relation between *People* and Improvement was not statistically significant at any level. Is this in accordance or not with what lean theory suggests? Certainly it is. Lean approach to human resources is concentrated on trying to obtain the best from workers through the involvement of everyone in the pursuit of perfection; in a lean enterprise everyone is aware of his/her own important role in achieving company's goals and is stimulated towards commitment and responsibility for the company's sake, not for a personal reward. From this point of view, indeed, reward and compensation do not foster the spirit of the group of workers that share knowledge and competences to constantly improve activities; they rather may have the opposite effect of growing individualistic behaviours among people, preventing the cooperation and communication, as it were an individual challenge between workers. The non-significant parameter between *People* and Improvement, in this sense, suggests that, in order to obtain relevant improvements in the operations, reward and compensation are not the right paths to follow; investing resources in such mechanisms might not be profitable, or, in worse cases, it can get the situation worse inhibiting that collaboration spirit that is precious in human resources management.

In the end, to sum up, we can say that for every company that approaches lean management and wants to fully exploit the benefits that this production system can bring, the necessity to build an appropriate framework is an unavoidable prerequisite. The adoption of single techniques (or bundles of techniques) that are part of the lean philosophy is not efficient if the overall company infrastructure is not adequate. This work stresses the attention on how tightly the infrastructural framework is related to real improvement achievements. Everything, from the general business strategy to the way every single activity is managed, have to be consistent and satisfactorily prepared in order to gain real and concrete benefits from the improvement initiatives and, in general, from the lean production system. These considerations, that might seem a little obvious, are particularly important because they are supported by data, thanks to the HPM project and to the statistical tools that Structural Equation Modeling makes available. It is only through these kinds of quantitative elements that these conclusions can be drawn with certain sureness. The potential benefits of data analysis like this one are really noteworthy, and everyone should be mindful of this. I really hope that, years by years, the elements of Structural Equation Modeling and, in general, of every statistical procedure may be always more helpful to provide a significant and quantitative support in the study of the lean management, both demonstrating its importance with a scientific approach and helping companies to exploit it in the best way possible.

Appendix

A1 Correlation matrix of the variables of the CI infrastructure

	Z	AA	AB	AC	AD	AF	AG	AH	AI	AJ	AK	AL	AM
Z	1												
AA	0.6208	1											
AB	0.3371	0.3609	1										
AC	0.4169	0.3639	0.6168	1									
AD	0.1145	0.0741	0.1440	0.1752	1								
AF	0.3209	0.2967	0.4681	0.5570	0.2226	1							
AG	0.3060	0.3283	0.5265	0.5378	0.0982	0.6168	1						
AH	0.2039	0.2205	0.1697	0.2843	0.0835	0.2208	0.2138	1					
AI	-0.3527	-0.3507	-0.2337	-0.3015	-0.0362	-0.2996	-0.2806	-0.4012	1				
AJ	0.3763	0.3769	0.3678	0.3595	0.0796	0.2864	0.3175	0.1900	-0.2738	1			
AK	0.3836	0.3429	0.3012	0.3682	0.0389	0.4287	0.3957	0.1850	-0.3332	0.1640	1		
AL	0.3959	0.3837	0.3371	0.3047	0.0443	0.3166	0.2617	0.2064	-0.2855	0.2715	0.2942	1	
AM	0.3376	0.3570	0.2105	0.2423	0.0533	0.2201	0.1917	0.2910	-0.3298	0.3112	0.2603	0.5255	1
AN	0.1900	0.1580	0.3454	0.2611	0.0426	0.2538	0.2694	0.1211	-0.1834	0.1866	0.1026	0.2552	0.0892
AO	0.4501	0.4537	0.2525	0.2559	0.0692	0.3277	0.2966	0.2609	-0.3295	0.2753	0.3394	0.3946	0.3766
AP	0.4680	0.4038	0.3422	0.2851	0.0498	0.3656	0.3451	0.2555	-0.3996	0.2940	0.3883	0.4408	0.4257
AQ	0.4170	0.4019	0.3482	0.3545	0.0102	0.3411	0.3246	0.1860	-0.3523	0.3071	0.3353	0.4512	0.4621
AR	0.3077	0.2932	0.4865	0.4690	0.1348	0.4529	0.4813	0.2380	-0.2608	0.3507	0.2558	0.2424	0.1921
AS	0.3415	0.3915	0.5504	0.5277	0.1427	0.5240	0.5923	0.2531	-0.3172	0.3564	0.3819	0.3032	0.1904
AT	0.3788	0.4035	0.2716	0.2377	0.0726	0.2685	0.2697	0.2276	-0.3317	0.3103	0.2712	0.3360	0.2347
AU	0.3828	0.3240	0.2478	0.2482	0.0535	0.2331	0.2208	0.2248	-0.3339	0.3136	0.2686	0.3173	0.2476
AV	0.3837	0.2975	0.3041	0.3118	0.1739	0.2952	0.2847	0.1963	-0.3332	0.2680	0.3770	0.2404	0.1557
AW	0.4292	0.3697	0.2876	0.2969	0.1311	0.3402	0.2795	0.1886	-0.3180	0.2633	0.3566	0.2533	0.1244
AX	0.4119	0.3042	0.3449	0.3575	0.1093	0.3277	0.2768	0.2334	-0.3657	0.2764	0.3570	0.2802	0.1508
AY	0.4793	0.4235	0.3484	0.3313	0.0689	0.3132	0.2768	0.2072	-0.3482	0.3071	0.3771	0.2921	0.2011
AZ	0.4251	0.4857	0.3494	0.3065	0.1040	0.3028	0.2792	0.2727	-0.3891	0.3325	0.3229	0.4043	0.2234
BA	0.4439	0.4217	0.3626	0.4003	0.1145	0.3631	0.3133	0.2297	-0.3831	0.3083	0.3554	0.4427	0.3312
BB	0.0945	0.2108	0.2547	0.1345	0.1549	0.0634	0.0426	0.0144	-0.1226	0.1243	0.0470	0.1038	0.0090

	AN	AO	AP	AQ	AR	AS	AT	AU	AV	AW	AX	AY	AZ	BA	BB
Z															
AA															
AB															
AC															
AD															
AF															
AG															
AH															
AI															
AJ															
AK															
AL															
AM															
AN	1														
AO	0.1086	1													
AP	0.1209	0.5629	1												
AQ	0.0890	0.5522	0.6769	1											
AR	0.2425	0.2673	0.3176	0.3458	1										
AS	0.2999	0.3552	0.3962	0.3153	0.6552	1									
AT	0.2182	0.3760	0.3972	0.3931	0.2627	0.3185	1								
AU	0.1732	0.2996	0.3937	0.3821	0.2614	0.3391	0.6749	1							
AV	0.2375	0.3230	0.3336	0.2665	0.4217	0.4178	0.4010	0.3973	1						
AW	0.2241	0.3088	0.3613	0.2712	0.3677	0.4133	0.4211	0.3660	0.7254	1					
AX	0.2129	0.3171	0.3528	0.2744	0.3318	0.3835	0.3885	0.3357	0.6703	0.7763	1				
AY	0.2034	0.3176	0.3375	0.2855	0.3522	0.4022	0.4232	0.3454	0.6227	0.7861	0.8144	1			
AZ	0.2028	0.4193	0.4381	0.4017	0.3485	0.3452	0.5441	0.3948	0.4123	0.4046	0.4779	0.4792	1		
BA	0.2406	0.4083	0.4321	0.4034	0.2974	0.3885	0.6066	0.5075	0.4840	0.4843	0.5282	0.5242	0.6794	1	
BB	0.2249	0.0403	-0.0213	0.0859	0.1351	0.1800	0.1567	0.1986	0.1646	0.1173	0.0986	0.0980	0.1587	0.1909	1

A2 Correlation matrix of the variables of Improvement

	A	B	C	D	E	F	G	H	I	J	K	L	M
A	1												
B	0.7799	1											
C	0.5348	0.5560	1										
D	0.8033	0.7891	0.5954	1									
E	0.2960	0.2372	0.3188	0.2949	1								
F	0.3713	0.2963	0.3106	0.3195	0.6985	1							
G	0.3338	0.2996	0.3637	0.4033	0.6450	0.6580	1						
H	0.2908	0.2599	0.3444	0.3243	0.5916	0.5477	0.5057	1					
I	0.3631	0.3325	0.3636	0.4030	0.3629	0.3178	0.3670	0.3342	1				
J	0.2706	0.2466	0.2546	0.2421	0.3640	0.3241	0.2998	0.3288	0.3416	1			
K	0.2934	0.2154	0.2483	0.2778	0.2622	0.2481	0.1937	0.2370	0.3324	0.4293	1		
L	0.3235	0.2711	0.2523	0.2377	0.3586	0.3353	0.3047	0.2955	0.3448	0.5199	0.4118	1	
M	0.3452	0.3136	0.3394	0.2940	0.3190	0.2950	0.2200	0.3251	0.3975	0.5034	0.4501	0.5360	1

Bibliography

Anand G., Ward P. T., Tatikonda M. V., Schilling D. A. 2009. *Dynamic capabilities through continuous improvement infrastructure*. Journal of Operations Management, 27, 444–461.

Bendoly E., Swink M., 2007. *Moderating effects of information access on project management behavior, performance and perceptions.* Journal of Operations Management 25 (3), 604–622.

Bessant J., Caffyn S., 1997. *High-involvement innovation through continuous improvement* International Journal of Technology Management 14 (1), 7–28.

Bollen K. A., 1989. *Structural Equation with Latent Variables*. New York, Wiley.

Bracalente B, Mulas A., Cossignani M., 2009. *Statistica aziendale*. McGraw Hill.

Browne, M.W., Cudeck, R., 1993. *Alternative ways of assessing model fit*. In: Bollen, K. A., Long, J.S. (Eds.), *Testing Structural Equation Models*. Sage, Newbury Park, CA, pp. 136–161.

Campbell D. T., Fiske D. W., 1959. *Convergent and discriminant validation by the multitrait-multimethod matrix*. Psychological Bulletin 56, 81–105.

Choo A.S., Linderman K.W., Schroeder R.G., 2007. *Method and context perspectives on learning and knowledge creation in quality management.* Journal of Operations Management 25 (4), 918–931.

Corbetta P., 2002. *Metodi di analisi multivariata per le scienze sociali*. il Mulino, Bologna, 2nd ed.

Flynn B. B., Flynn E. J., 2004. *An exploratory study of the nature of cumulative capabilities.* Journal of Operations Management 22 (5), 439–457.

Ghoshal S., Bartlett C. A., 1994. *Linking organizational context and managerial action: the dimensions of quality of management*. Strategic Management Journal 15 (5), 91–112.

Grandinetti R., 2008. *Marketing, mercati, prodotti e relazioni*, Carocci.

Grant R. M., 1991. *The resource-based theory of competitive advantage: implications for strategy formulation*. California Management Review 33 (3), 114–135.

Hammer M., Champy J. A., 1993. *Reengineering the Corporation: A Manifesto for Business Revolution*. Harper Business Books, New York.

Kraatz M. S., Zajac E. J., 2001. *How organizational resources affect strategic change and performance in turbulent environments: theory and evidence.* Organization Science 12 (5), 632–657.

Liker J. K., 2004. *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*. McGraw-Hill.

Mendelbaum G., 2006. *Keep your eye on the ball.* APICS Magazine, January 2006.

Peng D. X., Schroeder R. G., Shah R., 2007. *Linking routines to operations capabilities: A new perspective.* Journal of Operations Management, 26(6), 730–748.

Shah R., Goldstein S. M., 2006. *Use of structural equation modeling in operations management research: Looking back and forward*. Journal of Operations Management, 24, 148-169.

Slack N., Chambers S., Johnston R., Betts A., Danese P., Romano P., Vinelli A., 2007. *Gestione delle operations e dei processi*. 1st ed. Italy, Pearson Education.

Slack N., Chambers S., Johnston R., 2010. *Operations Management*. 6th ed., London: Financial Times, Prentice Hall, Pearson Education.

Teece D. J., Pisano G., Shuen A., 1997. *Dynamic capabilities and strategic management*. Strategic Management Journal 18 (7), 509–533.

Teece D. J., 2007. *Explicating dynamic capabilities: the nature and microfoundations of (sustainable)enterprise performance*. Strategic Management Journal 28 (11), 1319–1350.

Womak J. P., Jones D. T., Roods D., 1990. *The machine that changed the world*. 1st ed. New York: Rawson Associates.

Womak J. P., Jones D. T., 2003. *Lean Thinking: banish waste and create wealth in your corporation*. 2nd ed. New York: Free Press.

Wu C. W., Chen C. L., 2006. *An integrated structural model toward successful continuous improvement activity*. Technovation 26 (5/6), 697–707.

Zollo M., Winter S. G., 2002. *Deliberate learning and the evolution of dynamic capabilities.* Organization Science 13 (3), 339–351.

Acknowledgements

Nello scrivere la parte dedicata ai ringraziamenti mi prendo la piccola licenza di cambiare lingua e di scriverli in italiano, poiché in questo modo riesco a trasmettere meglio la mia riconoscenza alle persone a cui sto per rivolgermi.

Come d'obbligo, il primo ringraziamento lo faccio al mio relatore, il Prof. Andrea Furlan, che mi ha assistito durante tutta la preparazione della tesi con competenza, intelligenza e serenità. Un professore con la "P" maiuscola (che potrebbe non liberarsi tanto facilmente di me). Un grosso ringraziamento anche al prof. Adriano Paggiaro, per l'immensa disponibilità e l'aiuto nel risolvere i problemi relativi alla parte prettamente statistica della mia tesi.

Voglio ringraziare non solo i professori, ma tutto il personale della facoltà (o dipartimento, che dir si voglia) di Scienze Statistiche dell'Università di Padova; un modello di facoltà gestito perfettamente, a livello di formazione, supporto agli studenti e attrezzature per la didattica. Ricorderò sempre con tanta gioia e serenità questi anni trascorsi al Santa Caterina. Un grazie anche alla signora Delfina Di Monte, della segreteria, per le innumerevoli volte in cui le ho rotto le scatole.

Un immenso grazie, poi, a tutta la mia famiglia, tra cui i miei fratelli e la mia cara nonna, ma specialmente mia madre e mio padre, che mi hanno supportato in tutti gli aspetti durante questi anni della mia formazione universitaria. Senza di loro nessun traguardo sarebbe stato possibile. Un grazie perché so che fanno (e sempre faranno) il tifo per me.

Voglio ringraziare, poi, tutti i miei amici della "band": luca, gio, alice, kec, pera, obi, pava, lorenz (e relative morose); un gruppo di amici veri con cui ho trascorso tutta la mia giovinezza ed ho un grande bagaglio di ricordi uno più bello dell'altro (e spero di continuare a collezionarne tanti altri insieme). Un grazie speciale anche alla cara amica Arianna per tutta la compagnia dei mesi trascorsi da quando (con mia immensa fortuna) siamo diventati amici. Un grazie anche a tutti gli amici dell' erasmus e al mitico Walter del Pizzaflash.

Sempre tra gli amici, ringrazio tutti i miei compagni che ho trovato qui a Statistica, tutte persone eccezionali, ognuna per un motivo diverso; con loro ho condiviso tanto della mia

vita universitaria, dalle lezioni (spesso non senza qualche chiacchera o battuta di troppo), all’ansia per gli esami, alle partite a carte in aula studio, ai pranzi in mensa, a qualche weekend fuori porta. Tra tutti cito il trio bea-fede-marchio, ma soprattutto i carissimi Pietro e Nicola, non solo amici ma anche persone di grande spessore, da cui ho veramente molto da imparare.

Un grazie di cuore veramente a tutti.