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Transforming Management: An Empirical Study on the Impact of Firm Process Automation on Managerial Roles

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Abstract

This thesis aims to provide insights based on empirically validated data on whether the adoption of business process automation (BPA) tools within firms will require a shift on managerial activities and behaviors, so that better organizational performance will be achieved. The literature review and the statistical analysis are aimed at providing insights on what the new necessary skillsets and work patterns of managers will look like after automation is implemented, by means of Dubrin's framework for managerial roles (2012), also taking into account all the contextual factor that are needed to provide a detailed explanation of why and under which conditions certain roles are subject to change.

The analytical part of the study consists in an experimental, cross-sectional analysis, which makes use of a multiple regression model, which ultimately allows to quantify how much some of the managerial roles introduced by DuBrin (2012) are likely to change as a consequence of an increase in firm process automation. More specifically, the sample consists of 80 managers, all located in Italy, and spanning into medium-to-large organizations, and different hierarchical levels within their organizations.

The results show that automation does impact management in medium-to-large Italian firms, emphasizing more strategic tasks, albeit with a minimal impact as of today. More specifically, the variable that has been found to be affected by automation consists of establishing policies, rules, and procedures to coordinate the flow of work and information within the unit. On the other hand, in contrast with the literature findings, the hypotheses related to first-line and middle managers were found not to be significant.

As a result, in the future, managers are likely to face an increased importance of tasks such as designing the jobs of group members and clarifying group members' assignments, given the growth that process automation has been facing in the last few years, and its double-digit CAGR market. Managerial work is likely to move on from repetitive and routine tasks in the medium-long term, thus requiring individuals able to tackle more abstract matters, thus emphasizing the ability to think strategically and practically.

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Introduction

The literature gap that this study intends to address has first been addressed on Hales' paper on managerial work (Hales, 1986), where the author called for a more integrated approach that connects empirical evidence with theory to truly understand why managers behave as they do, moving beyond mere description to causal explanation. Building on this perspective, we apply his call to the domain of business-process automation, where understanding managerial behavior requires both empirical insight and theoretical grounding. More than three decades on, while academic literature primarily emphasizes technical and operational aspects, there is a considerable gap in understanding how such automation reshapes managerial responsibilities and workflows. This highlights a crucial area of inquiry: examining managerial adaptation and role evolution due to technological advancements. In this study, both qualitative and quantitative approaches are adopted: first, the most relevant themes for process automation are identified in the literature, afterwards they are tested using the theoretical lens of managerial roles. This approach allows us to show whether certain managerial sets of behaviors will be enhanced or diminished by means of process automation.

The central aim of this thesis is to examine how managerial roles, as defined by DuBrin's comprehensive 17-role framework, evolve due to increased business process automation within organizations. More specifically, the study investigates the impact of varying levels of process automation, by means of Robotic Process Automation (RPA) and Intelligent Automation (IA) on managerial roles across different hierarchical levels: top, middle, and first-line management. Therefore, the paper is primarily structured into two parts: the first one covers a comprehensive literature review, while the second focuses on empirical research.

The literature review will discuss key theoretical frameworks including DuBrin's managerial roles, as well as the reasons why these roles are subject to changes. Another key part of this work is about business processes and how they can be automated: this thesis delves deep into the matter, showing how to develop a firm-wide automation strategy, as well as how to select what should be automated and under which conditions, and finally showing a practical method on how that could be done. The study also addresses critical barriers to automation such as process fragmentation, implementation costs and skill shortages (Deloitte, 2022), alongside the influential concept of organizational agility.

The analytical component of this thesis makes use of a multiple regression model to quantify the probability and significance of automation-driven changes in specific managerial roles for both junior and middle managers. Here, process automation serves as the independent variable, and roles, identified by DuBrin's framework (2012) form the dependent variable. This empirical analysis also deploys organizational agility as a moderator variable, assessing how the shift occurs, given different possible levels of agility. Key themes anticipated from this analysis include the clear identification of roles most affected by automation, as well as highlighting differences across management's hierarchical levels.

The thesis then proceeds to discuss the interpretation of these findings within the context of the outlined theoretical framework, as well as the limitations of the study. The statistical model is first validated by assessing significance for the controlling variables, and afterwards the hypotheses are tested. The result section will therefore provide a nuanced understanding of how managerial roles adapt or evolve due to automation. The concluding chapter synthesizes key findings, highlighting the implications for management, and proposing directions for future research.

Section 1: Literature Review

Chapter 1: The Fourth Industrial Revolution Background

1.1 Fourth Industrial Revolution and the Automation Imperative

The world is in the midst of the Fourth Industrial Revolution (4IR) – an era defined by rapid, technological change that is progressively blurring the lines between physical and digital domains (WEF, 2016). Unlike prior industrial epochs, the 4IR is distinguished by its unprecedented velocity and scope, disrupting virtually every industry in every country. Emerging technologies such as artificial intelligence (AI), robotics and the Internet of Things (IoT) are fundamentally altering how organizations operate and compete.

Nowadays, technology adoption has become inseparable from strategy – companies now invest heavily in AI, data analytics, cloud platforms, and process automation not just for incremental gains, but to redefine the way they operate, and not face obsolescence as a consequence of falling behind in terms of innovativeness. One hallmark of the 4IR's impact on businesses is the rapid uptake of automation technologies – including AI, robotic process automation (RPA), and intelligent agents – to streamline tasks and augment human work. Unlike mere IT upgrades, thist type of transformation entails rethinking entire business models, as well as processes, to leverage digital capabilities, consequently demanding concurrent changes in organizational culture and structure.

Automation under the Fourth Industrial Revolution has become a multibillion-dollar juggernaut: the global Industry 4.0 market was valued at USD 164.7 billion in 2024 and is projected to reach USD 570.5 billion by 2033, with a CAGR equal to 14.44% (IMARC Group, 2024). Empirical research confirms that such transformation can strongly enhance firm competitiveness in areas such as customer service and procurement (BCG, 2025).

A striking case is Klarna's AI customer service assistant, launched in 2024, which within its first month handled a workload equivalent to 700 full-time human agents – all while maintaining customer satisfaction on par with human-provided service. Not only did this AI assistant resolve inquiries faster (often in under 2 minutes versus 11 minutes for human agents), but it also improved quality: repeat customer queries dropped by 25% due to more accurate resolutions (BCG, 2025).

Ultimately, companies today face an unavoidable automation imperative: with studies showing that up to 50 percent of industrial work can already be automated (de Jong, Lalla-Sewgoolam, & Vainberg, 2019) and 41 percent of manufacturers planning to invest in factory automation hardware within the next two years (Deloitte, 2025), organizations that delay risk ceding critical efficiency, cost, and innovation advantages to more agile competitors. Furthermore, early adopters report cost reductions of up to 30 percent and productivity gains exceeding 20 percent through strategic automation deployments (McKinsey & Company, 2020), underscoring that automation is no longer optional but essential for sustaining competitiveness in the Fourth Industrial Revolution.

1.2 Managing in the context of 4IR

As a result of the advent of the fourth industrial revolution, firms have all found themselves into a race where first-move innovators with high investments in intangible assets have faced huge success within their markets. A striking example of this dynamic is given by superstar firms (Autor et al., 2020), which are defined as large, highly productive companies characterized by strong investments in intangible assets, especially regarding information technology and R&D. Firms like Apple and Tesla are perfectly representative of this archetype. Indeed, these investments in long-term oriented strategic activities have allowed those firms to scale up quickly and efficiently, consequently outpacing smaller competitors. However, despite all the benefits and risks that may come with process automation, a practical issue now comes up for management: how do these innovations affect business-as-usual dynamics, and what is the new approach to effectively managing in this new context?

The answer to this question is complex and is not just a single one: a whole variety of different contingences need to be addressed, such as a manager's individual characteristics, what their job requires them to do and how the organization positions itself in the market and how it organizes its workforce with the objective of delivering value. According to Zhang's study on managerial role evolution over time (2023), for most of the twentieth century a manager's chief duty had been to "translate strategy into orders", making their work rooted into direct supervision, tight monitoring, and the power to discipline staff. Today, the same title signals almost the opposite: managers are prized for brokering information across functions, coaching teams, and knitting specialized knowledge into coherent solutions, especially in matrix or project settings where no single expert can see the whole picture. As a result, during the course of time, the role of managers has evolved from boss to bridge. The reasons behind this shift are many, but indeed, the most important factors were globalization and digitalization (Zhang, 2023). In the first case, product and project complexity exploded, forcing firms to rely on cross-functional teams that must be coordinated rather than commanded. Then, with the advent of new technologies, digital performance-tracking systems have automated much of the old monitoring burden, pushing managers to add value by fostering collaboration instead of enforcing compliance.

Chapter 2: Business Process Automation

2.1 Developing an automation strategy

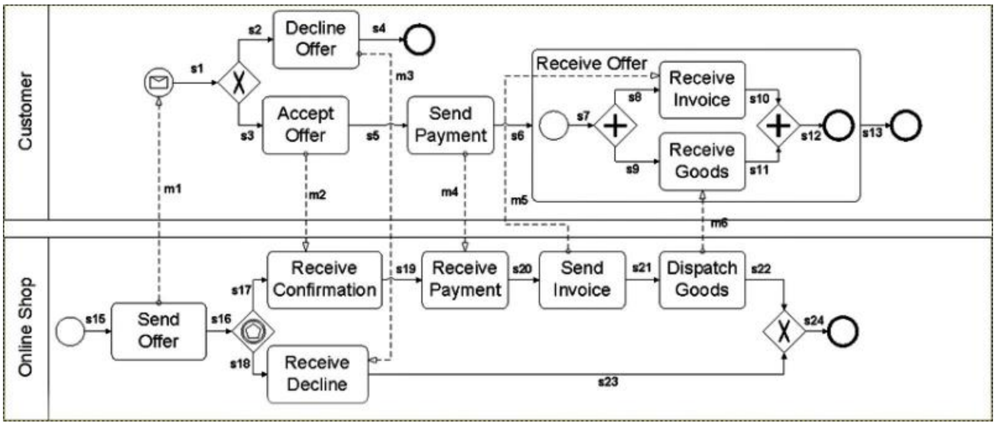
In order to put automation initiatives into practice, organizations should first start by defining the business outcomes they want to achieve: among the list of possible objectives there may be elements such as improving service quality, reducing costs, or enhancing employee satisfaction, or everything else that the overall corporate strategy may require in order to achieve a sustainable competitive advantage (Porter, 1985). This implies that firms will be constantly trying to make improvements to their most strategically relevant activities, also given the possible criticalities and difficulties they may be facing across the value chain.

To identify new opportunities for improvement, Flechsig (2022) suggests that corporate owners first provide a budget for automation efforts: this limits the perimeter of action, allowing them to prioritize the most important initiatives. Then, the author recommends assessing existing innovation trends, such as AI, and finding use cases of these technologies inside the organization. Once the main areas of interest within the value chain are identified and clearly defined, it is important for firms to investigate how processes work, as well as to identify innovation gaps, using either process-mining or discovery workshops. Doing so allows to both discover and prioritize opportunities that offer the greatest value given the least amount of effort, also known as quick wins.

2.1.1 Analyzing business processes with BPMN and process mining

According to the resource-based view (RBV), a firm's resources are the firm's stock of tangible, intangible and human assets (Barney, 1991), while capabilities are the organisationally embedded and non-transferable routines that allow a business to successfully perform a specific task or set of tasks (Makadok, 2001). Such routines take concrete form as business processes, which are defined as the stable, patterned sequences of activities that coordinate people, technology and information, with the aim of delivering a product or service to customers. The latter are therefore the real-world manifestation of how a firm links together its resources to achieve a final output: as a result, process proficiency becomes essentially the observable manifestation of a capability.

In practice, business processes consist of cross-functional workflows, which may extend across one or more supply chains, and aim to deliver value to the final customer (IMI, 1994). In his work, Davenport (1993) emphasizes the importance of process innovation and optimization for achieving competitive advantages and operational efficiency, stressing the fact that business processes must be clearly understood, measured, and managed systematically to ensure organizational success. To achieve so, processes have to be expressed in the business process model and notation (BPMN) graphical notation, a standardized framework for the graphical representation of business processes. The latter allows to understand what exactly happens across one or multiple supply chains, by means of representing all the tasks needed to deliver a product or service to the final customer (Owen, 2003).



Example of a process in BPMN. Adapted from Wong (2013).

According to BPMN syntax, all the elements need to be drawn inside of “swim lanes”: these represent graphically who’s responsible for each action and when. Then, circles denote events: the latter mark a significant moment on the process timeline. More specifically, a thin-border circle signals the start event, where a trigger such as a message, timer, or signal launches the flow. A double-border circle denotes an intermediate event that the process encounters while running; it can pause to “catch” something (for example, wait for a timer or incoming message) or “throw” something (such as sending a message or raising an error). A thick-border circle is the end event, which stops the path and can emit a result.

In the BPMN notation there is also the presence of gateways, which are drawn as diamonds, and decide how paths diverge or converge (Owen, 2003). A task is represented as a rounded rectangle and represents a single, atomic unit of work such as, for instance, baking a pizza. As soon as the latter is executed, control passes immediately to the next element. Finally, connections knit the diagram together: a solid-line sequence-flow arrow shows control passing from one element to the next inside a single participant; instead, a dashed message-flow arrow shows information exchanged between different participants (Owen, 2003).

Using the BPMN notation allows to analyze how exactly the delivery of a product or service to the final customer occurs and may show potential pain points and bottlenecks that occur during the process, by means of methods such as process mining (Van der Aalst, 2012). The latter consists in analyzing processes using detailed event logs that modern information systems (such as Salesforce, SAP etc.) record and associate to each task to be performed to carry out a process. By reading these time-stamped traces, process-mining algorithms can reconstruct a model of how a process really unfolds, compare that reality with a prescribed model, and then provide performance KPIs, highlight pain points, and show bottlenecks, as well as the processes' most frequent pathways to its end (Van der Aalst, 2012). This enables firms to find out where the main issues are occurring and why based on real data, allowing them to draw conclusions on how to intervene to fix any issues.

Therefore, understanding precisely how each process works is of utmost importance to understand where automation can be implemented and how, allowing firms to identify opportunities for improvement (Davenport, 1993). These processes, when clearly defined and optimized, provide an ideal foundation for business process automation, allowing organizations to streamline operations, reduce errors, and enhance productivity by leveraging technological advancements such as RPA and IA (Deloitte, 2015).

That is put into practice by means of matrix that evaluates each process based on two key dimensions: the level of effort required to address its pain points and the potential benefits that resolving those issues could bring. This approach involves assessing how complex or time-consuming it would be to implement changes (by means of automation or redesign), taking into account the costs associated with new implementations and weighing those factors against the expected outcomes, which could consist of cost savings, additional revenues and reducing organizational headcount (Badiru & Thomas, 2013). By plotting processes on this matrix, decision-makers can visually identify which processes offer the greatest return on investment with the least effort, helping to guide strategic choices in automation initiatives.

An impact–effort matrix places improvement ideas into four buckets:

1. Quick wins—high-impact, low-effort changes that should be implemented right away
2. Major projects—high-impact, high-effort initiatives that merit investment and careful planning
3. Fill-ins—low-impact, low-effort tasks that can be tackled when resources are free
4. Time-wasters (or thankless tasks)—low-impact, high-effort activities that are usually deferred or eliminated because they absorb resources without delivering commensurate value.

As specified beforehand, the most important of these opportunities are quick-wins: the latter in business-process management are defined as narrowly scoped, low-effort, low-cost and low-risk changes that the team can make within its own authority (Badiru & Thomas, 2013). They often deliver a visible, measurable benefit within a few weeks, without causing downstream problems. Because quick wins provide rapid, tangible results, they build momentum and credibility for the improvement program, create a safe-to-fail learning loop and can even generate savings that help fund larger redesign or automation efforts. Typical examples include removing unnecessary approval, adding a simple data-entry validation rule or re-sequencing tasks to eliminate idle time.

2.1.2 Choosing the right automation methods

Once the opportunities for improvement are identified, firms should carefully select the right automation tools and methods for each of the chosen areas of interest. By means of a literature review on the matter, Dirnberger-Wild (2024) provided a framework to help on the matter. According to the author, essentially two factors need to be assessed: the first factor suggested by the author is assessing whether the input data is structured or not. For instance, an example of structured data is event logs stored in a specific section within an ERP platform. On the other hand, unstructured data may consist, for instance, of a list of customer complaints received by email, which would need to be categorized with advanced instruments such as NLP algorithms and understood to then deal with the requests. Putting it simply, if the data already arrive in a predictable format, rules can be hard-coded, and the bot will run cheaply and reliably (Dirnberger-Wild, 2024).

The other factor to consider is process variability: the latter are described as workflows which have many possible ends to their completion, frequent exceptions, and decision logics that change with context (Dirnberger-Wild, 2024). As a result, there will be four possible outputs for the final choice in terms of which automation to choose:

- Structured Data + Low Process Complexity: Classic RPA scripts
- Structured Data + High Process Complexity: RPA plus workflow engine and exception-handling rules
- Unstructured / semi-structured Data + Low Process Complexity: RPA + point AI (e.g., NLP to process language)
- Unstructured / semi-structured + High Process Complexity: Intelligent Automation

The author finally suggests considering data availability: the latter allows for more accurate measurements before and after the automation occurs, allowing for better monitoring of the real impact of modifying a certain process (Dirnberger-Wild, 2024).

All these processes will then need to be implemented by means of a roadmap, which should prioritize the initiatives that are the most efficient to pursue, giving the highest value with a lower level of effort, as well as the ones with the highest strategic value, which may be harder to implement but are still of crucial importance in order to translate the initial strategy into competitive advantage.

2.1.3 Assessing costs, benefits and practicality of automation

Later on, quantifiable goals and metrics will have to be calculated for each project: these KPIs are often defined in terms of financial metrics and could consist of measures such as "cutting average claim-handling cost by 30 %". Setting "North-Star KPIs" like this one ensures that automation does not become an endpoint by itself, but a lever for strategic performance (Willcocks, 2016). Alongside financial metrics, companies may also track error-defect rates, customer Net Promoter Score, and qualitative metrics such as improvements in customers' perceived brand equity gains, to correctly assess the scale of their strategic choices (Willcocks, 2016).

Furthermore, to smoothen the execution of innovation projects, Flechsig (2022) suggests there being strong project-specific coordination efforts between the IT department and all the others that are involved: according to the author, doing so would foster better innovation outcomes and reduced lead times by as much as 30-50%, compared to traditional handoffs. While developing an automation strategy, Willcocks (2016) also suggests assessing existing automation efforts that either exist on that process or other related ones, which may have scale-up potential. The author suggests that re-using existing components had cut development effort by 30-40 % at a European utility company, making every subsequent project quicker and cheaper. As a result, Willcocks suggests that the more a firm automates, the easier the scaling of existing innovation will become.

In line with this reasoning, some organizations may even implement a "Center of Excellence" talent model, where a core expert team develops reusable components and supports business-led automation teams with coaching and standards (Willcocks, 2016). These centers' scope would revolve around sharing knowledge across the organization (e.g. communities of practice for automation), becoming a point of reference for the organization, helping it learn and improve gradually over time to improve future projects' outputs (McKinsey & Company, 2020).

The literature on the matter also suggests that addressing both organizational readiness and cultural acceptance is a crucial factor in facilitating adoption (Dirnberger-Wild 2024); recent work on organizational digital-transformation readiness shows that, beyond technology, firms must cultivate supportive leadership, a digitally literate workforce and an agile, learning-oriented culture if they are to translate investment into sustained value (McKinsey & Company, 2023). Positive experiences with new tools do more than smooth the transition: they create “pull” effects that encourage experimentation and continuous improvement for both blue and white-collar workforce, amplifying the benefits of digital transformation initiatives (Deloitte, 2022).

2.2 Automation methods for Business Processes

Contemporary process optimization frameworks increasingly rely on integrating Business Process Model and Notation (BPMN) with advanced analytics to systematically address bottlenecks. By analyzing event logs derived from BPMN-designed workflows, organizations can employ process mining techniques to map deviations between idealized process models and real-world execution patterns. This data-driven approach identifies critical pain points, such as prolonged cycle times in approval workflows or recurrent errors in data entry, which traditional process mapping often overlooks. Once bottlenecks are pinpointed, redesign may occur by means of either simplifying the process or using tools to automate one or more tasks, provided that doing so will be beneficial for the firm.

Dirnberger-Wild (2024) provided a framework to match the type of automation to each process: the first element to consider is how frequent exceptions are: that is, how much the process is likely to take turns on its way to completion. Among the principal methodologies identified in the literature, Robotic Process Automation (RPA) and Artificial Intelligence (AI) coupled with Machine Learning have garnered considerable attention due to their potential to fundamentally enhance process efficiency and organizational performance.

RPA consists of algorithm-based robots that interact with digital systems to automate standardized, repetitive, rule-based processes, such as transferring information between applications (Deloitte, 2015). The latter is deemed to be suitable for processes that are methodical and consistent, offering benefits like reduced costs, improved accuracy, and enhanced employee morale by freeing staff from tedious tasks (Deloitte, 2015). For instance, an RPA bot can automatically watch for incoming order emails, extract key data, enter it into the company's ERP system, and send confirmation messages—reducing manual order-entry time by up to 85% and virtually eliminating data-entry errors (Willcocks, 2016).

On the other hand, the use cases for intelligent automation (IA) differ drastically. IA builds on RPA by integrating cognitive technologies (like AI, machine learning, natural language processing) to automate more complex, nonroutine tasks that require judgment, intuition, or problem-solving (Deloitte, 2015). The latter enables enterprises to tackle complex processes, that traditional RPA alone cannot handle (IEEE, 2019). For this type of automation, use cases span from non-routine day-to-day operations to possibly managing processes from start to finish, that being defined as end-to-end (E2E), (Deloitte, 2015). An example of this would be a call-center voice bot, which is able to listen to the customers, categorize requests and respond, using NLP to understand customer queries such as "Why is my bill higher this month?". The bot would then retrieve account data via API calls, and either provide an immediate answer or delegate complex issues to a human analyst.

As mentioned previously, business process automation, whenever possible, contributes positively to firm performance, possibly bringing strong benefits in terms of cost-efficiency, quality and process safety (McKinsey & Company, 2023). The latter could therefore be a strategic asset for a firm, provided that a careful cost-benefit analysis is carried out and that all the potential risks are taken into consideration.

Despite the benefits of adopting RPA and IA technologies, Deloitte's Global Intelligent Automation Survey (2022), identifies a series of barriers, which may undermine this approach. According to the study, the main factor causing issues with process automation is the fact that in firms there are often processes that are difficult to manage with a unified flow: this results in a series of interdependences with multiple owners which may have differing objectives, creating complexity for the scaling of business process automation (Deloitte, 2022). Also, the fact that most firms lack individuals with the skills to engineer innovation are another relevant negative factor, largely attributable to two factors: the scarcity of top-notch workers in the field of AI, and the fact that smaller organizations often find it harder to recruit top-level talents as opposed to first-in-class firms. Lastly, one of the biggest issues is bearing the costs associated to innovate processes, since developing in-house solutions, especially if there’s a lack of qualified personnel and IT infrastructure is often costly in terms of time, money and effort (Deloitte, 2022). Moreover, automation-as-a-service providers, as well as outsourcing, may not always give solutions tailored to the needs of firms: as a result, most firms will find it more convenient to craft in-house solutions rather than accessing the market and possibly facing high transaction costs.

2.3 Building an agile organization

Bridging the fields between business process automation and managerial roles is organizational agility; the latter is defined by McKinsey & Company as the ability of a firm or single business unit to quickly reconfigure its strategy and people, allowing it to respond nimbly to external contingences (McKinsey & Company, 2017).

Agile is not simply an iterative or creative process; it is a holistic, systematic method designed to overcome common barriers to innovation by empowering small, cross-functional teams to work in short, transparent cycles, continuously prioritizing customer value and adapting based on empirical feedback (Bain & Company, 2015). Central to Agile is the sprint, a time-boxed iteration (typically one to four weeks in length), during which a cross-functional team works toward a clear, focused objective and produces a potentially shippable product increment (Schwaber & Sutherland, 2011).

At the start of each sprint, a multidisciplinary team collaboratively defines the “sprint goal”: a concise statement that guides decision-making and keeps the team aligned. Although the latter remains fixed once the iteration begins, the team retains flexibility in scope: they may refine or replan the work items as new information emerges, so long as the Sprint Goal remains attainable (Schwaber & Sutherland, 2011).

Evidence from both the software industry and broader business applications demonstrates that agile practices can dramatically improve success rates, speed to market, team morale, and customer satisfaction. As organizations face increasingly volatile markets and shifting customer demands, organizational agility has become a critical competency for sustained innovation and competitive advantage.

The adoption of these principles fundamentally reorients managerial responsibilities in the context of automation: agile enterprises flatten hierarchies and form cross-functional, self-managing teams, changing the manager's role from controller to coach (Bain & Company, 2015). Rather than issuing directives, managers in agile settings empower teams and act as servant leaders – influencing through coaching and development rather than hierarchical authority. Decision-making becomes therefore decentralized: those closest to the work gain authority to make day-to-day decisions, dramatically speeding up response times. As a result, Bain & Company observes that agile practices free senior managers from micromanaging, enabling them to spend more time strategizing, removing impediments and fostering cross-functional collaboration (Bain & Company, 2015).

The agile approach however does not imply there being a full-adaptation approach towards the competitive environment: in fact, according to McKinsey & Company's "How to build an agile organization" report, an organization's agility based on two key dimensions: stable practices and dynamic practices.

Stable practices are those that provide reliability, efficiency, and a consistent backbone for the organization. These include standardized ways of working, shared digital platforms, cohesive communities, and clear leadership structures. Stability ensures that certain core elements do not need to change frequently, supporting scale and operational excellence. Dynamic practices, on the other hand, enable speed, responsiveness, and adaptation. Examples include rapid iteration and experimentation, continuous learning, flexible resource allocation, and information transparency (McKinsey & Company, 2017). These practices empower organizations to sense and seize new opportunities, respond quickly to changes, and innovate effectively. As a result, after assessing whether a given firm or business unit scores high in either of those practices, agility can be assessed. More specifically:

- High stability and high dynamism: These are truly agile organizations, excelling at both reliable operations and rapid adaptation.
- High stability but low dynamism: Such organizations are often bureaucratic—efficient but slow to adapt.

- High dynamism but low stability: These resemble start-ups—fast-moving but potentially chaotic and lacking in reliability.
- Low stability and low dynamism: These are “trapped” organizations, neither efficient nor adaptable.

In conclusion, building an agile organization helps in quickly taking advantage of innovation opportunities and in reacting quickly to external contingences as soon as they manifest. Furthermore, the importance of direct monitoring efforts is diminished because of managing a cross-functional, self-motivating team which can be monitored using digitalized tools such as digital dashboards and continuous interactions. As a result, larger organizations have lately started to adopt a model in which the junior managers’ role becomes to directly monitor team operations, address technical challenge related to projects and restoring order in case crises and disruptions were to manifest themselves during everyday activities (Zhang, 2023).

Chapter 3: Managerial Roles

3.1 Managerial roles taxonomy

The lenses that this study uses to explain how managerial responsibilities evolve as a function of an increase in process automation is given by the body of theory of managerial roles. The approach of this thesis is to work with a set of given behaviors, which provide a perimeter for the analysis, while also allowing to evaluate what exactly is likely to change because of a heightened level of business process automation. The underlying assumption is that, once processes are innovated, managers may face the need to adapt to the new changes, as a consequence of innovation “disrupting” certain areas of their work, and opening doors for other productive activities. Therefore, using existing managerial role sets allows to examine variations in behavioral frequences, by applying a comprehensive and theoretically robust set of constructs, thus ensuring to provide precise directions for the managers of the future.

With regards to this academic field, Mintzberg’s 1968 doctoral thesis fundamentally challenged prevailing myths about managerial work by using structured observation to study what managers do in their workplace (Mintzberg, 1968). Earlier perspectives, such as those by Henri Fayol (1916) and Frederick Taylor (1911), emphasized managerial tasks through principles of planning, organizing, commanding, coordinating, and controlling. Fayol outlined managerial work explicitly as systematic and structured functions, whereas Taylor introduced scientific management, which saw managerial responsibilities primarily as task optimization and efficiency maximization (Taylor, 1911).

Subsequent studies began to challenge these formalistic views by highlighting the complexity and structured nature of managerial tasks. Chester Barnard (1938) significantly influenced the field by emphasizing the role of communication, cooperation, and informal organization, suggesting that managerial work involves coordination through social systems rather than task oversight. Peter Drucker (1954) further contributed to understanding managerial work by emphasizing managerial decision-making, effectiveness, and goal setting. Drucker, as opposed to the other authors, focused less on prescriptive functions and more on how managers accomplish objectives through decision processes and strategic thinking.

Mintzberg's approach differed significantly from these earlier authors in its methodology and perspective. While earlier theories typically proposed normative frameworks or idealized managerial tasks, the author conducted detailed empirical observations of managers in action. In his study, the findings show that managerial work is "hectic, fragmented, and action-oriented" (Mintzberg, 1968). This implies that constant interruptions have to be faced by managers, and a wide variety of brief activities need to be handled, with little time for sustained reflection or planning.

Based on his doctoral thesis, Mintzberg developed a framework for managerial roles in a later study in 1973. The author describes the latter as "those categories of actions and behaviors associated with managers' job performance" (Mintzberg, 1973). These consist of 10 roles divided into 3 categories: interpersonal, informational and decisional. According to the author:

- Interpersonal roles involve interacting with people both within and outside the organization.
- Informational roles pertain to gathering, disseminating, and processing information.
- Decisional roles involve making decisions and choices affecting organizational resources and directions.

Later, Andrew DuBrin's approach (2012), while also being based on structured observation, placed greater emphasis on managerial competencies and skill sets required for effective management. The author categorizes managerial roles more explicitly around leadership functions, interpersonal relations, and personal skills development. Unlike Mintzberg, who highlighted the fragmented and reactive nature of managerial tasks, this more recent study provided a more structured framework focused on practical managerial skills and developmental guidelines for effective leadership performance.

The model that this thesis uses for the analysis is therefore the latter (DuBrin, 2012), which adds on another 7 roles to Mintzberg's 10. The newly found patterns were then divided into four categories: planning, organizing and staffing, leading, and controlling. Planning, according to the author, consists in setting strategic and operational directions, while organizing and staffing focus on coordinating resources and managing personnel.

Leading encompasses motivating, coaching, and guiding teams, and controlling involves monitoring activities, solving problems, and handling disruptions (DuBrin, 2012).

The author also provided detailed descriptions for each of these roles and what each of these entails:

Role Category	Role Name	Description
Planning	Strategic Planner	Sets the long-range direction by analysing the external environment, crafting vision, and formulating corporate-level strategy.
	Operational Planner	Breaks strategy into day-to-day budgets, schedules, and short-term goals for units or projects.
Organizing and Staffing	Organizer	Designs the structure: groups activities, defines reporting lines, and establishes workflows.
	Liaison	Builds and nurtures a network of internal and external contacts to secure information and
	Staffing Coordinator	Works with HR to hire, place, and develop the right people; manages succession planning.
	Resource Allocator	Divides up money, people, equipment, and time among competing demands.
	Task Delegator	Assigns responsibilities and authority to subordinates and follows up on progress.
Leading	Motivator & Coach	Inspires performance, provides feedback, removes obstacles, and builds skills and
	Figurehead	Performs ceremonial and symbolic duties such as signing contracts or hosting visitors.
	Spokesperson	Communicates the team's plans, results, and needs to senior leaders, media, or regulators.
	Negotiator	Bargains with customers, suppliers, unions, or peers to reach favourable agreements.
	Team Builder	Fosters group cohesion, recognises contributions, and shapes team norms.
	Team Player	Cooperates laterally, shares information, and supports cross-functional work.
	Technical Problem Solver	Applies specialised expertise to troubleshoot operational issues.
	Entrepreneur	Spots opportunities or threats and initiates change—new products, processes, or ventures.
Controlling	Monitor	Tracks performance metrics and environmental signals, compares them with plans, and flags
	Disturbance Handler	Takes charge during crises, conflicts, or disruptions, restoring order and adjusting plans as

DuBrin's 17-role framework. Author's personal elaboration (2025)

With this framework, it is possible to highlight which role category will be enhanced or diminished by automation, after using both qualitative and quantitative approaches.

3.2 Explaining variance in managerial roles

According to Mintzberg (1973), there will indeed be variations in the way managers enact interpersonal, informational and decision-making roles: as a result, the latter may only be understood as a product of a multi-level conditioning system. The author suggests that roles should be interpreted within firm and individual-specific context, which allows us to explain which behaviors will be the ones enacted by individual managers, as well as the underlying motivation of them occurring (Mintzberg, 1973).

3.2.1 Hierarchical level and organizational structure

At the structural level, hierarchical position remains the most powerful differentiator: the literature on the matter clearly identifies roles specific to each hierarchical level that managers could be divided into. These three levels are the following: top, middle and junior management, each having its own purpose inside organizations.

According to Kraut et al. (2005), first-level managers typically focus on individual supervision: their tasks are often related to managing individual performance, enacting behaviors such as motivating employees, resolving performance issues and instructing subordinates by means of training or just breaking down work assignments. On the other hand, the middle managers' main function is to link groups and allocate resources. Middle managers emphasize tasks such as establishing targets, estimating resource needs and translating downwards the top management's directives. Another essential function of this group is acting as a broker between top management and lower levels, as well as managing group performance by defining responsibilities and informing managers of performance goals. Finally, executives were identified to have two main functions: monitoring the external environment and consequently providing strategic guidance. Other relevant activities for this group include developing relationships with customers/vendors and participating in task forces for new opportunities (Kraut et al., 2005).

Adding on to this matter, Mintzberg also suggests that decisional roles may be distributed differently given different organizational structures: for instance, those that place strong emphasis on hierarchy will ensure top managers have strong decisional responsibilities. Furthermore, for more hierarchical organizations, managerial roles and responsibilities are most likely to be clearly defined even for junior and middle management, with little room for variability. Instead, in the case of more organic and innovative organizations, roles will instead have the highest variability given each possible managerial level, with decision-making authorities shifting more towards the lower-level managers (Mintzberg, 1973).

3.2.2 Firm size and environmental complexity

Among other factors, Mintzberg (1973) also suggested that firm size and environmental complexity are also able to affect the mix: as organizations grow, monitoring and coordination become more specialized and entrepreneurial initiatives often migrate to discrete staff units. For smaller firms, instead, roles and responsibility are less defined, with owners often performing a wide variety of roles themselves. This “jack of all trades” behavior means they frequently step in to replace employees or handle operational tasks directly (Floren & Tell, 2004). Adding on to the matter, highly competitive industries privilege information-processing roles, while routine, low-growth industries accentuate control-oriented behaviors. As a result, environmental complexity increases the frequency by which scanning and disseminating information occurs (Gibbs, 1994).

3.2.3 Managerial job description

Another factor predicting managerial roles variation are the limits built into each job itself: the latter places a boundary for possible individual behaviors, showing which roles could be manifested in the workplace, but without addressing behavioral frequency. The leeway for managerial action has however been addressed by Stewart’s “demands, constraints and choices” model (Stewart, 1982). In her framework, “demands” refer to the essential duties and responsibilities that must be performed, “constraints” denote the factors that limit what a manager can do (such as organizational rules, resource availability, or superior expectations), and “choices” represent the areas in which managers have discretion to decide how to act. This last dimension suggests that managers often face a varying degree of subjectivity in responding to various situations, resulting in behavioral patterns that may differ significantly across individuals. For instance, one may prefer delegation to solve certain issues, whereas another may prefer taking on the matter by themselves. Again, this model is useful to understand what the perimeter of action for managerial roles is but does not explicitly quantify frequencies of behaviors.

3.2.4 Organizational culture and personality traits

Moving back to Mintzberg’s work (1973), the author also suggests that organizational culture amplifies some roles and lowers the saliency of others, conferring legitimacy on particular behaviors. To operationalize these dynamics, DuBrin (2012) distinguishes three ideal-typical archetypes: experimental cultures privilege continual invention and rapid iteration, positioning managers as entrepreneurial coaches who discover opportunities and foster learning and innovation practices. Instead, bureaucratic cultures value stability, consistency and risk containment; managers here serve primarily as monitors, coordinators and resource allocators, enforcing rules and auditing performance. Finally, Clan cultures are built on shared values, loyalty and mentorship, casting managers as mentors and team builders who foster relationships, facilitate consensus and model the organization’s core values. Importantly, DuBrin states that the managers absorb cultural norms, yet they also shape them, with managerial influence on corporate values intensifying as hierarchical level increases.

Individual personality traits also affect managerial action: Hales (1986) demonstrated that the Big 5 personality traits can influence a manager’s preference for certain roles, especially distinguishing between informational and interpersonal domains. Each trait exists on a spectrum, with people varying in how strongly they express each one. The traits are represented on a growing scale as follows (Rammstedt, 2007):

Conscientiousness – impulsive, disorganized vs. disciplined, careful

Agreeableness – suspicious, uncooperative vs. trusting, helpful

Neuroticism – calm, confident vs. anxious, pessimistic

Openness to Experience – prefers routine, practical vs. imaginative, spontaneous

Extraversion – reserved, thoughtful vs. sociable, fun-loving

According to Neal (2011), the personality traits associated the most with job performance were found to be conscientiousness and neuroticism: the first has a strong positive effect on task proficiency, whereas the latter was found to have a negative one, on that same indicator. Similarly, DuBrin (2006) has contributed to the matter by integrating personality and leadership theory into the analysis of managerial behavior, stating that effective leaders are meticulous in their work and show higher levels of emotional intelligence, thus reflecting the importance of these two dimensions in managerial work. Furthermore, the author analyzed each of these traits' implications in terms of leadership style: first, extraversion tends to be associated with interpersonal roles, whereas conscientiousness supports planning, organizing, and control-based roles. Openness to experience facilitates innovation and entrepreneurial behavior; agreeableness instead enhances teamwork and interpersonal harmony. The author further contends that effective leadership depends on the fit between a manager's personality and the prevailing culture: if both variables are compatible with each other, they will become a strong predictor for both the repertoire of roles enacted and the leadership style adopted.

3.2.5 Functional specialty

Finally, Kraut et al. (2005) explored the impact of functional specialty, identifying it as a secondary but still discernible source of variation in managerial role priorities. For instance, according to the authors, marketing managers may attach the greatest weight to outward-facing roles, whereas administration managers place comparatively more importance on instructing subordinates, yet they rate representing staff and monitoring the environment lowest. The authors concluded that these variations, related to functional specialty, were found to be present but still noticeably smaller than the differences associated with hierarchical level (Kraut et al., 2005).

Managerial role categories therefore remain analytically useful only when interpreted through this contingent lens: the apparent variability in managerial work is not random but results from a series of structural, contextual and personal factors that collectively define what it means to "manage" in any given setting.

3.3 Automation's impact on managerial roles

Given their functional specialty and hierarchical level, managers need to abide with a set of duties based on how their skillset can help the company in correctly exploiting these new resources that have been acquired, which enable process automation and all the benefits that come with it. By means of an extensive literature review on the matter, Lippert (2024) discovered that roles involving routine, repetitive, or data-driven tasks (e.g., monitoring employee performance, scheduling), are highly likely to be replaced by AI systems. On the other hand, however, according to the same author, those that require interpersonal interaction such as motivating employees, conflict resolution is less likely to be fully automated and are better suited for collaboration between human managers and AI. As a result, according to McKinsey & Company (2023) managers are held accountable for the evolution and training of their workforce in more innovative scenarios. Instead of watching people drop out of the workforce from discouragement, their role should be to help midcareer workers reinvent themselves and try to pull in people who fear or resist change. Also, according to the author, some roles face a medium risk of automation: certain roles remain (as of now) firmly within the human managerial domain but are expected to increase in importance as AI adoption grows, such as strategic decision-making and ethical oversight (Lippert, 2024).

Adding on to the matter, Zhang's study on managerial role evolution highlighted, based on an extensive analysis of job postings from the 1940's to current times, an ever-increasing need for interpersonal skills regarding middle and junior managers' job descriptions (Zhang, 2023). According to the author, both tiers are moving away from the old monitoring-heavy duties, going towards a role focused on teamwork and coordination, though the change is stronger for middle managers. More specifically, Zhang shows that from 2007 to 2021, the share of middle-manager positions asking for teamwork skills jumped from 13 % to 32 %, while mentions of direct supervision fell sharply. Résumés and employee reviews tell the same story: middle managers now spend more time linking different teams, guiding staff, and keeping projects on track. Albeit later, first-line managers' responsibilities are moving in the same direction: demands for collaboration have roughly doubled and demands for close supervision have dropped and the qualifications required for monitoring roles are now getting lower due to the presence of digital dashboards and data visualization tools (Zhang, 2023).

The author also suggests this move happens faster in companies that stress innovation and research: the more a firm's ads talk about innovation, the more they ask managers to collaborate rather than supervise. As a result, middle managers have changed the most, yet junior managers are clearly following, turning both roles into facilitators instead of overseers and reshaping how workplace hierarchies function. Overall, the literature on management role change seems to agree that activities that require strategic decision-making and interpersonal skills are unlikely to be replaced in the short term. Instead, activities such as monitoring and scheduling face a higher risk of automation, allowing managers to delegate these tasks to other colleagues or machines, so that they can focus on more value-adding activities.

Section 2: Methodology

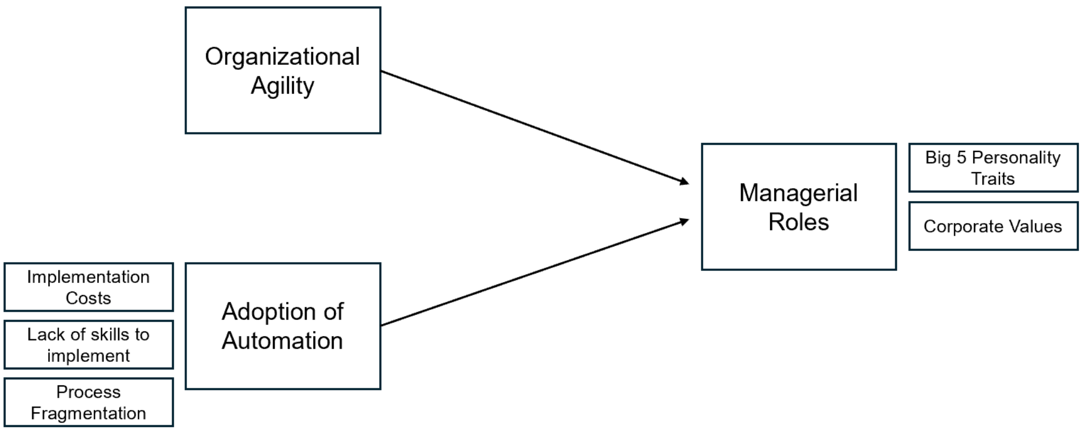
Chapter 4: Research Design

4.1 Design and hypothesized model for the study

This study employed a cross-sectional, experimental design to examine the effects of process automation on managerial roles. A quantitative approach was adopted to assess relationships between variables through multivariate regression analysis.

The sample consists of 80 managers employed at medium to large firms located in Italy. Participants included junior, middle, and top-level managers across a variety of industries. Eligibility criteria required that participants hold a current managerial position, and all data has been collected in April 2025, using a structured online survey which has been designed to explore multiple dimensions related to the impact of technological change on managerial roles. Specifically, it included sections addressing the extent of process automation within the organization, the Big Five personality traits of the respondents, perceived organizational agility, common barriers to implementing automation, and changes in managerial roles. The methods of response consisted primarily of closed-ended questions and standardized Likert-scale items.

Given the extensive analysis performed in the literature, the hypothesized model to apply for the analysis is as follows:



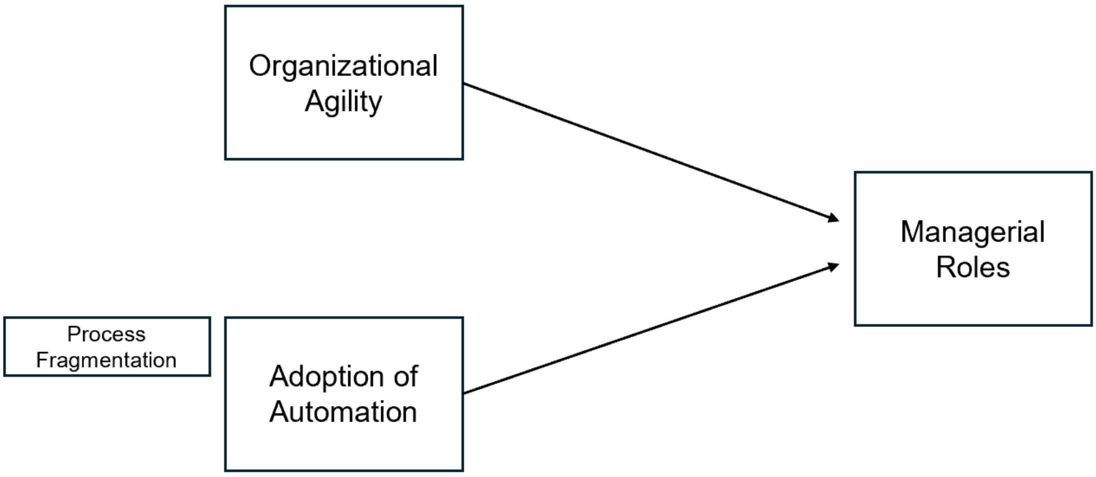
Automation alone is likely to explain only a minimal portion of the variance in managerial roles enacted, since processes are managed by the employees which perform working tasks every day and only affect managerial work indirectly. Therefore, a variable which helps analyze the impact on managerial roles, still based on innovative efforts, is organizational agility. The latter would also lead to a reduced omitted variable bias (OVB) and is likely to have a higher predicting power than automation, since it would have a more direct effect on a manager's work. In fact, it has been found that under varying levels of agility, management may stick more either towards interpersonal or direct supervision tasks. Moreover, this addition allows to deduct whether the dependent variable is more likely to be related to a variation in automation or agility, by addressing significance for each variable.

Looking at the model, the primary independent variable is the degree of process automation, measured through the self-reported level of process automation perceived by managers inside the organization. The dependent variable was defined as the self-reported time spent on each of DuBrin's managerial roles. Again, the aim of the study is to find out whether, given a specific sample, one or more sets of roles are subject to change, given varying levels of process automation. Controlling roles were attributed to variables affecting the adoption of process automation in the first place, the most important being process fragmentation, cost of implementation and lack of personnel to implement. These factors may skew how much a firm adopts automation in the first place, correcting for factors such as firm differences in size, as well as the extent to which processes are fragmented (and thus harder to automate within a unified flow) and complex. In fact, some organizations may be operating in less dynamic contexts, where activities show little variation and optimal procedures are known and mapped. Controlling for the variables highlighted beforehand would allow for an unbiased comparison, despite there being differences in context, size and workforce skills.

Other controlling variables were used regarding managerial roles and were shown to affect leadership styles and differing best practices across organizations. The variables chosen were therefore personality, measured using BFI (Big 5 Inventory), and corporate values, measured using Li's map for corporate values (2021). A moderating role was attributed to organizational agility since it is hypothesized that under varying levels of the latter, management may stick more either towards interpersonal or direct supervision tasks.

4.2 Model deployed for the study

Despite the hypothesized model having a stronger predictive power and providing a more comprehensive explanation of what exactly happens as different variables interact with each other, the samples collected required the latter to be simplified. A general rule of thumb for statistical analyses is to have 10 observations for each of the variables present in the research model. Also, due to the hardships in reaching the right respondents for the study, 80 observations have been collected, and once managers are split into different hierarchical levels, the number of data collected drops significantly. As a result, an optimal model for the analysis will consist of 3 variables and will allow them to capture causal relationships, without injecting excessive measurement noise into the analysis.



This final model considers what has been deemed to be the most relevant barrier to process automation, that being the fragmentation in terms of ownership of said processes (Deloitte, 2022). By creating a variable that considers the interaction between how much firms make use of automation and how present these barriers are, it becomes possible to highlight what the real level for that dependent variable is: doing so would therefore showing how much an organization has innovated having faced the issue of process fragmentation.

To carry out the analysis, quantitative data were analyzed using SPSS 29. A multiple linear regression model was deployed to assess the predictive effect of process automation and organizational agility on managerial roles. Statistical significance was set at $p < .05$ for all analyses, meaning that the dependent variable is assumed to be significantly altered for p-values lower than this threshold. Finally, the fact that managerial roles largely differ give different hierarchical levels led to the use of three different samples for the analysis: the same model has been adopted for all the hypotheses, ensuring a better coherency of the study and of the results.

4.3 Limitations of the study

This study faces several limitations to keep in mind. First, the findings rely heavily on each manager's own impressions when judging the degree and impact of automation in their workplace. A first difficulty arises since these assessments are subjective: as a result, two managers in similar situations may rate automation differently, injecting noise and potential bias into the results.

Another limitation is given by the hardships faced in reaching the respondents: the Italian market presents many small firms, in which managerial responsibilities are less defined as opposed to bigger firms, which have instead been chosen to populate the sample. Also, reaching higher level managers turned out to be demanding, especially for executives, leading the sample to have just enough observations to test first-line and middle managers' hypotheses. As a result, the study does not formulate hypotheses on how top management may change their work pattern as a consequence of an increase in automation. This is due to the fact that only 19 observations were collected, well below the 31 middle-manager and 30 junior-manager cases, and the author judged that sample too small to support reliable statistical tests. Consequently, the paper can describe how middle and first-line managers are changing but cannot confidently say whether CEOs and vice-presidents are experiencing specific shifts in responsibilities, authority, or required skill sets.

Also, the fact that the Italian market is being analyzed comes potentially with a series of complications. According to the 2024 European Innovation Scoreboard, Italy is classed as a "Moderate Innovator," scoring just 89.6 % of the EU average (rank 20 of 27) and investing only 1.45 % of GDP in R&D, compared with 2.2 % across the EU and 2.7 % across the OECD (OECD, 2024). Since product and process innovation diffuse more slowly in this environment, the demand for boundary-spanning "collaborator" managers is likely to emerge later, producing smaller effect sizes than those reported for high-innovation contexts such as the United States.

4.4 Research question reiteration and hypotheses

The research question this thesis aims to answer is as follows:

RQ: How will managerial roles, identified by DuBrin's framework, evolve because of an increase in process automation within a given firm?

To answer the question, all the underlying hypotheses are formulated, based on the most recurring findings that have been retrieved from literature. The hypotheses consist, respectively, of a general one which is valid for all managers, regardless of their hierarchical level, and some that are level-specific and valid for either one between middle or junior managers.

General Sample Hypothesis:

H1: Because of processes being automated, the "Organizer" role will be enhanced

This first hypothesis expresses the application of managers having a more strategic role as a consequence of automation: more specifically, it implies that managers who face higher automation levels in their organization will dedicate more time towards the orchestration of their organization's human resources and information streams, suggesting their time spent doing this strategic-value adding task will increase.

For Middle Managers:

H2: The "Liaison" role will be enhanced as process automation increases

H3: The "Monitoring" role will diminish as process automation increases

The second hypothesis implies that middle managers will emphasize more their broker-like role in the organizational structure, becoming an even more important link between top managers and lower organizational levels. Afterwards, the third hypothesis postulates that the simplification of monitoring activities, attributable to digital tools that enable real-time updates on operations, will allow middle managers to reduce their time spent performing this task. Both of these hypotheses are grounded in theory, according to what Zhang (2023) suggested.

For First-line Managers:

H4: The "Motivator and Coach" role will be enhanced as process automation increases

According to McKinsey & Company's study (2023) on GenAI and the future of work, managers will be expected to indulge more in training and interpersonal exchanges with their subordinates as automation increases. This hypothesis would be in line with an enhancement of personal and communication skills, because of the increasing automation, an aspect that is widely cited inside literature.

Section 3: Results, Discussion and Practical Implications

Chapter 5: Data Analysis and Results

5.1 Data Overview

After collecting the data regarding the hypothesized model, the findings related to each of the analyzed variables are represented as follows:

Variable	N	Average	Std dev.
Extraversion	80	2,70	0,782
Agreeableness	80	1,63	0,560
Conscientiousness	80	3,63	0,787
Neuroticism	80	1,71	0,692
Openness	80	3,27	0,807
Strategic planner	80	5,08	1,251
Operational planner	80	5,15	1,424
Organizer	80	5,38	1,129
Liaison	80	5,56	1,404
Staffing coordinator	80	4,91	1,608
Resource allocator	80	4,93	1,491
Task delegator	80	5,53	1,387
Entrepreneur	80	5,28	1,475
Figurehead	80	4,00	1,876
Disseminator	80	4,69	1,762
Negotiator	80	4,51	1,721
Motivator and coach	80	5,45	1,211
Team builder	80	5,81	1,213
Team player	80	5,80	1,036
Technical problem solver	80	5,36	1,343
Monitor	80	5,51	1,169
Disturbance handler	80	5,20	1,496
Integrity	80	4,15	0,800
Quality	80	4,18	0,742
Respect	80	4,19	0,670
Teamwork	80	4,14	0,638
Organizational Agility	80	3,77	0,599
Automation	80	5,58	1,777
Implementation costs	80	4,14	1,697
Process fragmentation	80	4,66	1,517
Lack of specialized workforce	80	4,05	1,771

With regards to the Big 5 inventory, the literature findings seem to hold: the Conscientiousness variable scores the highest in its category, reflecting pragmatism and better job performance, which are in line with the ideal characteristics of a manager.

Instead, the least prominent factor is neuroticism, which shows the lowest value among Big 5 indicators: this aligns well with DuBrin's findings, which emphasized that managers should maintain emotional stability to perform at their job.

On the other hand, the 17 managerial roles have registered a higher variance, compared to the other variables. However, this cluster of variables largely depends on factors such as hierarchical level, personality and culture and organizational context. Also notably, corporate values all have high scores, given their measurement scale going from 1 to 5. The measurement comes from the constructs being mentioned more often in Fortune 500 companies' earnings reports (Li, 2021); therefore, the results seem to show that the value clusters of "Integrity", "Quality", "Respect and "Teamwork" may be commonalities for several different companies nowadays, due to the high mean values and a smaller standard deviation compared to other variables.

Finally, perceived automation and its barriers were the ones showing the most differences in judgement as the high standard deviation shows. The latter are in fact assessed based on subjective metrics such as personal experience and personal knowledge on the matter of automation tools.

5.2 Analysis of Variance (ANOVA)

Following Mintzberg's assumptions (1973) on role differences across hierarchical levels, the table located below shows an ANOVA analysis made by grouping observations based on the three hierarchical levels taken into consideration.

	Type	Sum of Squares	DF	Avg of Squares	F	Sign.
Strategic planner	Between Groups	11,971	2	5,985	4,13	0,02*
	Within Groups	111,579	77	1,449		
	Total	123,55	79			
Operational planner	Between Groups	3,704	2	1,852	0,911	0,406
	Within Groups	156,496	77	2,032		
	Total	160,2	79			
Organizer	Between Groups	1,642	2	0,821	0,638	0,531
	Within Groups	99,108	77	1,287		
	Total	100,75	79			
Liaison	Between Groups	10,499	2	5,25	2,784	0,068
	Within Groups	145,188	77	1,886		
	Total	155,687	79			
Staffing coordinator	Between Groups	5,961	2	2,98	1,157	0,32
	Within Groups	198,427	77	2,577		
	Total	204,388	79			
Resource allocator	Between Groups	5,381	2	2,691	1,217	0,302
	Within Groups	170,169	77	2,21		
	Total	175,55	79			
Task delegator	Between Groups	6,313	2	3,157	1,669	0,195
	Within Groups	145,637	77	1,891		
	Total	151,95	79			

The table shows what has been categorized by DuBrin as "Planning" and "Organizing and Staffing" roles. Some of them differ significantly given different managerial hierarchical levels. For instance, the strategic planner role, which is based on envisioning long-term strategic initiatives for the firm is found to be either higher or lower for at least one group in comparison to the others. Then, the "Liaison" role comes close to having a significant difference, however it does not make the cut due to the significance threshold being set at $p<.05$, precisely capturing observations which stand at a 2 standard deviation distance from the mean.

The second table, located in the next page, proceeds to show the ANOVA analysis for the "Leading" and "Controlling" role categories.

	Type	Sum of Squares	DF	Avg of Squares	F	Sign.
Entrepreneur	Between Groups	9,835	2	4,918	2,336	0,104
	Within Groups	162,115	77	2,105		
	Total	171,95	79			
Figurehead	Between Groups	48,857	2	24,429	8,209	0,001***
	Within Groups	229,143	77	2,976		
	Total	278	79			
Disseminator	Between Groups	43,047	2	21,523	8,199	0,001***
	Within Groups	202,141	77	2,625		
	Total	245,188	79			
Negotiator	Between Groups	41,927	2	20,964	8,405	0,000***
	Within Groups	192,06	77	2,494		
	Total	233,988	79			
Motivator and coach	Between Groups	7,578	2	3,789	2,696	0,074
	Within Groups	108,222	77	1,405		
	Total	115,8	79			
Team builder	Between Groups	1,443	2	0,722	0,484	0,618
	Within Groups	114,744	77	1,49		
	Total	116,187	79			
Team player	Between Groups	4,261	2	2,131	2,037	0,137
	Within Groups	80,539	77	1,046		
	Total	84,8	79			
Technical problem solver	Between Groups	8,764	2	4,382	2,523	0,087
	Within Groups	133,724	77	1,737		
	Total	142,487	79			
Monitor	Between Groups	3,917	2	1,959	1,449	0,241
	Within Groups	104,07	77	1,352		
	Total	107,988	79			
Disturbance handler	Between Groups	8,239	2	4,12	1,882	0,159
	Within Groups	168,561	77	2,189		
	Total	176,8	79			

Looking at this table, several variables come close to having significant differences from the mean but do not end up making the cut: roles like “Motivator and coach”, as well as “Technical problem solver” show consistent deviations, but not enough for them to differ significantly. On the other hand, “Figurehead”, “Disseminator” and “Negotiator” feature extremely low and significant p-values. The first and third of the roles just mentioned (i.e. Figurehead and Negotiator) are more typical for a top-level manager, since they consist, respectively, of part-taking into ceremonial duties and handling negotiations on behalf of the firm. The “Disseminator” role consists instead of distributing important information to subordinates that would otherwise be inaccessible to them. This last role, as well as the previously cited ones, are soon to be analyzed by means of more detailed tables.

5.3 Managerial role variance across hierarchical levels

The tables below delve deeper into the ANOVA findings, allowing for a comparison between role averages across the three different groups that are being considered in this study.

First Line Manager	N	Average	Std. dev.
Strategic planner	31	4,68	1,351
Liaison	31	5,68	1,492
Figurehead	31	3,39	1,909
Disseminator	31	4,32	1,469
Negotiator	31	4,26	1,843
Motivator and coach	31	5,06	1,436
Technical problem solver	31	5,03	1,378

Middle Managers	N	Average	Std. dev.
Strategic planner	30	5,10	1,213
Liaison	30	5,13	1,383
Figurehead	30	3,77	1,775
Disseminator	30	4,23	2,029
Negotiator	30	3,97	1,586
Motivator and coach	30	5,67	0,959
Technical problem solver	19	5,37	1,049

Executives	N	Average	Std. dev.
Strategic planner	19	5,68	0,885
Liaison	19	6,05	1,129
Figurehead	19	5,37	1,257
Disseminator	19	6,00	1,000
Negotiator	19	5,79	0,976
Motivator and coach	19	5,74	1,046
Technical problem solver	19	5,89	1,049

Consistent with expectations, the "Strategic Planner" function achieves its highest observed value among Executives, decreases markedly among Middle managers, and registers its minimum level within First-line management. Also, in contrast with the literature on the matter, the prominence of the "Liaison" function appears attenuated among middle managers when compared to the other samples. Furthermore, a marked difference can be found for “Disseminator” and “Negotiator”, suggesting that executives might both possess and spread critical and difficult-to-access information across the organization, and are the ones mainly in charge of performing negotiations on behalf of their firm.

5.4 Hypothesis Testing

After deploying the model chosen for the analysis, data has been analyzed using SPSS 29’s linear regression function. The tables below show different outputs, including the coefficients, their significance level and the VIF indicator for multicollinearity, which is expected to be below 10 for all the analyses.

The hypotheses were successfully tested with said tool, yielding different results.

H1: Because of processes being automated, the “Organizer” role will be enhanced

	B	Std. err.	t	p-value	VIF	R-squared
(Constant)	3,463	0,766	4,521	0,000***		0,131
Automation with fragmentation	0,02	0,009	2,134	0,036*	1,156	
Organizational Agility	0,365	0,215	1,694	0,094	1,156	

The composite variable given by the interaction of automation with process fragmentation is shown to have a minimal but significant effect on the “Organizer” variable, which in turn is not affected significantly by organizational agility.

The second and third hypotheses refer to middle managers. Listed below are the results for the second and third hypotheses (H2, H3):

H2: The “Liaison” role will be enhanced as process automation increases

	B	Std. err.	t	p-value	VIF	R-squared
(Constant)	3,253	1,686	1,930	0,064		0,105
Automation with fragmentation	0,027	0,025	1,092	0,284	1,110	
Organizational Agility	0,491	0,480	1,024	0,315	1,110	

H3: The "Monitoring" role will diminish as process automation increases

	B	Std. err.	t	p-value	VIF	R-squared
(Constant)	4,994	0,766	1,365	0,001***		0,059
Automation with fragmentation	-0,025	0,009	0,02	0,221	1,110	
Organizational Agility	0,311	0,215	0,388	0,430	1,110	

After analyzing the data, despite the being strong theoretical evidence in the literature for middle managerial role evolution, the hypotheses do not hold for a strengthened "Liaison" and weakened "Monitor" role.

Finally, the hypothesis related to first-line management is analyzed:

H4: The "Motivator and Coach" role will be enhanced as process automation increases

	B	Std. err.	t	p-value	VIF	R-squared
(Constant)	7,270	1,499	4,849	0,000***		0,048
Automation with fragmentation	0,017	0,02	0,860	0,398	1,299	
Organizational Agility	-0,487	0,444	-1,098	0,282	1,299	

After data analysis, neither process automation or organizational agility seem to have a causal effect on the "Motivator and coach" role for the first-line managers' sample.

Discussion and Practical Implications

This study featured a literature review that has bridged multiple academic fields characterized by little connection with each other. All the hypotheses have been formulated based on these findings, ensuring they were grounded in theory, thus allowing for the statistical analyses to exclude any spurious relationships. In this context, managerial roles have proved to be useful as theoretical lenses to try and understand how managers may respond because of an increase in process automation. However, the fact that the analysis has been carried out with a relatively small sample has weakened the statistical robustness of the initial model: as a result, the survey has collected more data than what has ultimately been used in this analysis.

Even so, these observations were still used to make simple analyses and to validate theoretical constructs found in the literature: as a result, the descriptive statistics showed that certain managerial roles, which have not been tested, do vary along with hierarchical level: the first finding uncovered by this study is that managers belonging to different hierarchical level and organizational contexts have their own predominant functions, as well as other marginal ones. More specifically, the study shed light on C-level executives having as their predominant responsibilities to represent the organization, providing strategic guidance and handling negotiations on behalf of their company.

Afterwards, a significant relationship was found between process automation and the responsibility of managers to define how work and responsibilities are structured inside the organization. This finding shows that after automation is implemented inside an organization's production or service delivery workflows, managers may, in the future, have more space to dedicate themselves to more strategic and value-adding tasks, which in this case include the establishment of policies, rules, and procedures to coordinate the flow of work and information within business units or across the organization.

Despite the relationship strength of this relationship being very small, this result should be interpreted by looking at the long term: the entire market of automation is in constant expansion, featuring a double-digit CAGR, and is tagged to the fourth industrial revolution, which features technological trends that are growing unprecedently fast. If AI keeps improving at such a rapid pace and it were to increase its accessibility and efficacy, then a progressive and constant adaptation to these new conditions will be needed: this would imply that firms may find themselves adjusting their organizational structure, as well as the personnel inside the organization's job requirements and responsibilities accordingly to how their business model changes during the course of time, due to the presence of rapidly-growing technologies.

As a result, this study contributes to the literature by showing what one of future trends of management will be, shedding light on what is expected to change in terms of managerial job descriptions as companies keep reducing their output-to-headcount ratios, due to technological advancements progressively displacing repetitive and manual work and moving towards taking over more complex tasks. A key practical implication for managers in the future is for their job to become progressively more strategically oriented and possibly centered towards the human aspect of the job, despite this study not having empirically validated this last hypothesis.

Conclusion

In this thesis, we explored how business process automation reshapes managerial roles through the lens of DuBrin's framework. By combining a qualitative review of existing literature with a quantitative multiple-regression analysis, we sought first to identify the primary constructs that scholars have associated with automation and management, and then to empirically verify which of those constructs hold explanatory power when automation intensity varies. The core objective was to determine how increased automation reshapes what managers focus on day to day, and—drawing on DuBrin's categorization of managerial functions—to understand which managerial responsibilities are most amplified or diminished as organizations automate routine processes.

We also examined how to design and implement an automation strategy, highlighting steps such as assessing current processes, selecting appropriate technologies, and closely collaborating with key stakeholders during all the phases of the envisioned changes' implementation. Drawing on best practices found in the literature, we showed that an agile approach to automation—characterized by rapid iteration, continuous feedback, and cross-functional collaboration—helps managers anticipate and address role-related challenges early. This ensures smoother transitions for employees and allows managers to proactively reshape job descriptions and training programs before new workflows are fully implemented. By integrating DuBrin's theoretical framework with practical recommendations, the study illustrates how the "organizing" and "planning" functions of management evolve: instead of merely overseeing tasks, managers become architects of human capital, aligning talent strategy with automated systems.

Despite focusing primarily on medium-large sized firms in Italy, our findings underscore a broader trend: automation intensifies the need for managers to develop skills in job analysis, competency modeling, and change management. Organizations that fail to support this shift risk sidelining their managers, whereas those that provide training and foster agile practices can leverage managerial talent as a source of competitive advantage. Although the cross-sectional design limits causal inference, our work lays a foundation for future longitudinal studies and broader industry comparisons.

Ultimately, this dissertation demonstrates that business process automation does not render managers obsolete but rather transforms their roles from process overseers into strategic architects of work. As automation continues to advance, the capacity of managers to redefine workforce structures, clarify responsibilities, and champion agile practices will determine whether their organizations thrive in the digital age.

Appendix

Independent variable (IV):

Adoption of automation within the organization, 1-9 Likert scale

- Imagine an ideal organization transformed by intelligent automation. Compare your organization to that ideal by rating it on a scale of one to nine (one indicating ‘not close at all’ and nine indicating ‘very close’).

Deloitte (2022). Automation with intelligence. Deloitte’s Global intelligent automation survey, 7. Retrieved from https://www2.deloitte.com/content/dam/insights/us/articles/73699-global-intelligent-automation-survey/DI_Automation-with-intelligence.pdf

Barriers to adopting intelligent automation, 1-7 pt. Likert scale

When trying to implement innovation within the firm, how frequent are the following issues?

- Process fragmentation
- Lack of skills to implement
- Implementation costs

Deloitte (2022). *Automation with intelligence*. Deloitte’s Global intelligent automation survey, 7. Retrieved from https://www2.deloitte.com/content/dam/insights/us/articles/73699-global-intelligent-automation-survey/DI_Automation-with-intelligence.pdf

Organizational agility (given by the presence of a high number of both dynamic and stable practices).

Dynamic practices enable companies to respond nimbly and quickly to new challenges and opportunities. To what extent are the following practices adopted in your organization? 1-5 pt. Likert scale

- Information transparency
- Rapid iteration and experimentation
- Technology, systems, and tools
- Role mobility
- Continuous learning
- Open physical and virtual environment

Stable practices cultivate reliability and efficiency by establishing a backbone of elements that don't need to change frequently. To what extent are the following practices adopted in your organization? 1-5 pt. Likert scale

- Shared vision and purpose
- Standardized ways of working
- Cohesive community
- Performance orientation
- Actionable strategic guidance (i.e. the extent to which strategic plans can be operationalized)
- Entrepreneurial drive as a cultural aspect (i.e. innovation, proactiveness and risk-taking)

McKinsey & Company. (2017). *How to create an agile organization*. Retrieved from https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/how-to-create-an-agile-organization

Dependent variable (DV):

Managerial Roles, 1-7 pt. Likert scale

1. Strategic Planner: Focuses on long-term goals and strategies for the organization.

2. Operational Planner: Deals with short-term planning and day-to-day operational tasks.

3. Organizer: Structures resources and processes to achieve organizational objectives.
4. Liaison: Builds and maintains relationships inside and outside the organization.
5. Staffing Coordinator: Ensures the organization has the right personnel in place.
6. Resource Allocator: Determines how resources such as time, money, and personnel are distributed.
7. Task Delegator: Assigns tasks to team members effectively.
8. Figurehead: Represents the organization in ceremonial or symbolic roles.
9. Spokesperson: Communicates information about the organization to external stakeholders.
10. Negotiator: Handles negotiations on behalf of the organization.
11. Motivator and Coach: Inspires employees and helps them develop their skills.
12. Team Builder: Creates cohesive teams that work well together.
13. Team Player: Collaborates effectively within teams to achieve goals.
14. Technical Problem Solver: Addresses technical challenges and provides solutions.
15. Entrepreneur: Identifies opportunities for innovation and initiates changes or new projects.
16. Monitor: Collects and analyzes information to assess organizational performance or identify issues.
17. Disturbance Handler: Resolves conflicts, crises, or unexpected problems within the organization.

DuBrin, A. J. (2012). *Essentials of management*. South-Western.

Personality (Big Five), 1-5 pt. Likert scale

Instruction: How well do the following statements describe your personality?

I see myself as someone who…

1. is reserved
2. is generally trusting
3. tends to be lazy
4. is relaxed, handles stress well
5. has few artistic interests
6. is outgoing, sociable
7. tends to find fault with others
8. does a thorough job
9. gets nervous easily
10. has an active imagination

Scale: 1 (Disagree strongly), 2 (Disagree a little), 3 (Neither agree nor disagree), 4 (Agree a little), 5 (Agree strongly)

Scoring: Extraversion: 1R, 6; Agreeableness: 2, 7R; Conscientiousness: 3R, 8; Neuroticism: 4R, 9; Openness: 5R; 10 (R D item is reversed-scored).

Reference: Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of research in Personality*, *41*(1), 203-212.

Corporate values, 1-5 pt. Likert scale

The following are words frequently associated to specific corporate values: how much does your company's culture resonate with each of those values?

Innovation:

- Creativity
- Innovation

- Know-how

Integrity:

- Accountability
- Responsibility
- Trust

Quality:

- Dedication
- Quality
- Commitment

Respect:

- Empowerment
- Employee
- Culture

Teamwork:

- Engage
- Team
- Coordination

Li, K., Mai, F., Shen, R., & Yan, X. (2021). Measuring corporate culture using machine learning. *The Review of Financial Studies*, *34*(7), 3265-3315.

Manager’s hierarchical level, MC with a single answer

- First-line manager (Supervisor, team leader, associate director, office manager)
- Middle manager
- Manager of a small subsidiary
- Corporate officer (C-level, VP, Associate director, General Manager)

Kaiser, R. B., & Craig, S. B. (2011). Do the behaviors related to managerial effectiveness really change with organizational level? An empirical test. *The Psychologist-Manager Journal*, *14*(2), 92-119.

De Oliveira, J., Escrivão, E., Nagano, M. S., Ferraudo, A. S., & Rosim, D. (2015). What do small business owner-managers do? A managerial work perspective. *Journal of global entrepreneurship research*, *5*, 1-21.

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