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THE EFFECT OF GENERATIVE ARTIFICIAL INTELLIGENCE ON MANAGERIAL BEHAVIOR ACROSS FUNCTIONS

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Abstract

GAI is becoming readily available and easily accessible for those who are willing to take advantage of it. As a result, the world is witnessing a transformation regarding how managers perform their daily tasks. This study aims to understand the relationship between managerial behaviors and how they are changing with GAI use at the interaction and automation base of managerial roles. We collected a sample of fifty participants and administered a survey to analyze whether they are utilizing GAI and experience performance increase, whether they are exposed to technostress and whether managers are willing to adapt to the technology. We created four constructs based on EFA analysis and looked for relationships between gender, degree of education, firm size, and managerial roles for target constructs. No significant relationship was found between these categories. A similarity in responses between managerial roles was observed, indicating that different job titles do not create a strong categorization. Overall, these results suggest that managerial behaviors in Turkey may not be subject to change with the introduction of GAI.

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Chapter 1
A general look on Generative Artificial Intelligence

Our lives are changing. Humankind is surrounded by smart entities that are performing tasks of the past on their behalf. They are in our houses, streets, pockets, slowly entering our body and, as expected, in our work. With the formation of this collective memory that we call the internet, we enabled an infamous, sometimes dystopic phenomenon which is called man vs. machine. Generative Artificial Intelligence (GAI) is a fascinating realm, and we are about to delve into it. Our aim is to provide point of view of its development, capabilities, applications, implications, it's future and issues surrounding it. We will explore this transformative technology through distinct subtopics, each shedding light on a critical aspect of GAI. They will serve as a basis for our future discussion regarding the effects of GAI on management and employees.

1.1 Managerial Behavior and Strategic Decision Making in the Pre - Artificial Intelligence Era

Before we start our discussion, we would like to remind you how human progression looks like regarding decision making. It must track back all the way back to very beginning of our evolution. For instance, supervision goes back to keeping other humans around a campfire to prevent them getting lost in the dark, choosing a cave to hide in the night can find its appearance in where to set up the company since in both situations humans tried to understand the correct ground to settle. We have been making decisions to survive since we develop life. We have had managers since the very first forms of communities found formation. It is not possible to track the entire human decision-making development process, therefore we will fast forward time to a more relevant key moment.

At this point, it is a common knowledge that the progress of humanity is incomparable with pre 20th century. Most of the development we are enjoying happened in a very little amount of time when we think about how old the world and human history really is. Therefore, our classifications will stress the latter part of our history.

- **Pre 20th century :** Decisions were made by manual record keeping, collective discussions, with the help of basic calculators, mostly experience based, intuitive.
- **20th century :** Introduction of computers were groundbreaking. 1950's was one of the key milestones of decision-making progress. It enabled scientists to encrypt and decrypt highly complex equations. From now on, decisions will be kept and aided by enhanced machines, aka computers.
- **1970s – 1980s :** At this stage, computers proved themselves to be highly functional and many programs to help managers were also emerging. As an umbrella term, Management Information Systems (MIS) were introduced with the ability to organize data in a structured way and allowed managers to access it while also being able to generate basic reports (Laudon & Laudon, 2015).
- **1990s :** Enterprise Resource Planning (ERP) Systems stretched the informed decision-making of managers by combining different business functions together and created a streamline of information flow with advanced reporting capabilities. With ERP, managers now could supervise the entirety of the business and managers became much more analytical than they ever were. Strategic decision-making witnessed improvements on a massive scale (Davenport, 1998).
- **Early 21st century :** This can be considered as the current era; the technological advancements are mesmerizing more than ever. The amount of data in the world drastically increases day by day and managers meet with concepts such as Business Analytics, Big data, Predictive Analytics' improvements performed by machine learning and algorithms and finally, Artificial Intelligence and Generative Artificial Intelligence. Strategic decision-making responsibility seems like finally became lighter on managers' shoulders.

As these forms a basis, we will start our discussion with the GAI landscape since this thesis focuses on the effects of it on managerial behavior.

1.2 Overview of the Technology

A good start to have a look at the GAI landscape is its history. Generative models have a long history in artificial intelligence, dating back to the 1950s with the development of Hidden Markov Models (HMMs) (Knill & Young, 1997) and Gaussian Mixture Models (GMMs) (Reynolds, 2009), highlighted in the research (Cao et al., 2018). Hidden Markov

Models can be simplified as a probabilistic modal where from the given the dataset it can predict a sequence of upcoming values. Gaussian Models, on the other hand, with the given set, help the user to find out underlying patterns by simplifying the set into a mixture of Gaussian distributions. These early models were instrumental in generating sequential data such as speech and time series. However, it wasn't until the emergence of deep learning, which can be summarized as teaching a computer to learn and understand things by showing it lots and lots of examples, that generative models witnessed significant advancements in performance.

With the introduction of sequential data, AI moved into Natural Language Processing which is where the technology found it’s start as the way we recognize it today. Simply, it is a field of artificial intelligence that aims to teach computers interact with human language, recognition of the language and understanding the underlying meaning while predicting answers. A conventional approach for sentence generation involved learning word distributions using N-gram language modeling (Bengio et al., 2003) and subsequently searching for the optimal sequence. However, this method faced challenges in effectively adapting to longer sentences.

Progress ensued with the introduction of Long Short-Term Memory (LSTM) (Graves & Graves, 2012) and Gated Recurrent Unit (GRU) (Dey & Salem, 2017) architectures, which harnessed gating mechanisms to regulate memory during training and marking a substantial improvement over N-gram language models. To have a better understanding of these concepts, given the prompt to ChatGPT *“LTSM explained simply”* the answer received is “in the world of computers, LSTMs are used in tasks like understanding and generating text, recognizing speech, and even predicting future values in things like stock prices or weather.” (ChatGPT, personal communication, September 10, 2023).

So, in simple terms, LSTM functions as a smart reading companion that remembers, forgets, and understands the story in a book (or data) over a long period, making it great for tasks that involve understanding sequences of information. As GRU is very similar, it is a more simplified approach and is easier to train and faster due to the fewer parameters it contains. ChatGPT explains N-Gram models as those that “... are used in things like predictive text on your phone, spell checkers, and even in some machine learning tasks. They're like detectives who rely on patterns of words to make educated guesses about what comes next in a sentence.” (ChatGPT, personal communication, September 25, 2023).

A pivotal moment in the evolution of generative models arrived in 2014 with the introduction of Generative Adversarial Networks (GANs) (Goodfellow et al., 2014) showcasing remarkable results across diverse applications. ChatGPT's explanation of GANs is enlightening. If we imagine a creator and an inspector regarding cat drawings, creator will keep creating cat drawings and will get better and better at it while the inspector will keep distinguishing the fake drawings from the real cat pictures until the creator is excellent and the distinguishment is quasi-impossible. The emergence of transformer-based models like these marked a revolution in AI generation (ChatGPT, personal communication, September 25, 2023).

Another approach that evolved naturally regarding machine learning is Reinforcement Learning from Human Feedback (RLHF). Despite the developments made in Generative AI, challenges persist in aligning AI-generated content with human preferences and have meaningful interactions. To bridge this gap, reinforcement learning from human feedback (RLHF) has been deployed to refine models (Cao et al., 2018). This approach, applied across various applications, including Sparrow, InstructGPT, and ChatGPT, the pioneers of GAI and it encompasses two crucial steps. The integration of reinforcement learning from human feedback further refines AI's ability to align with human preferences, enriching our digital landscape (Aydın, 2023; Cao et al., 2018; Peñalvo & Ingelmo, 2023).

Initially, a language model is pre-trained on extensive datasets, serving as the foundation for the upcoming tasks. However, the prompt-answer pairs generated by this model may not always align seamlessly with human intent. Consequently, the second step involves training a reward model capable of encoding nuanced human preferences. In this process, different generated answers undergo evaluation by humans in a pairwise manner, extracting valuable feedback to enhance AI-generated content (Cao et al., 2018).

To understand the way that how these two approaches distinguish from one another is that, while GANs are to generate texts, data, images, videos etc., with the dataset they studied, in the case of RLFH, the focus shifts into training the Artificial Intelligence by professionals to perform better with human interaction and the method is rewards and feedback.

As the developments in the technology opens the way for human interaction with the GAN and RLFH models, the next focus is to enlarge the capabilities and catch excellence regarding the products of the models, therefore a significant focus has been placed on training more sophisticated generative models on substantially larger datasets, coupled with the utilization of larger foundational model architectures as mentioned before. This paradigm shift is observable in the transition from the GPT-2 to GPT-3 framework. While the primary framework architecture remains largely unchanged, the magnitude of improvement is evident in the expansion of pre-training data from WebText, which specifies the collective content in the World Wide Web, (Gokaslan et al., 2019), encompassing 38 GB of data, to CommonCrawl, which is a web archive project that regularly crawls and stores datasets of webpages, (Brown et al., 2020) which totals an impressive 570 GB after filtering. Additionally, the foundational model size has experienced an exponential increase, surging from 1.5 billion parameters to an astonishing 175 billion. Consequently, GPT-3 has demonstrated superior generalization capabilities compared to its predecessor, GPT-2, particularly in tasks such as human intent extraction (Cao et al., 2018).

Moreover, it is noteworthy that recent years have witnessed substantial hardware advancements that have significantly facilitated the training of large-scale models. An important recall here is that the mundane task of training large neural networks using central processing units (CPUs) was consuming long computational times. These hardware improvements have not only accelerated the training process but have also paved the way for more ambitious experiments in the AIGC domain (Cao et al., 2018).

Another topic that carries importance is the nature of GAI. The term 'generative' itself implies the capacity to produce or create something. In the context of AI, this definition applies broadly to various models, as they inherently "*produce* or create *something*". This can manifest as numerical predictions or internal rules, showcasing AI's innate ability to generate outputs. If we consider a calculator and if we prompt an equation the calculator will generate a response, yet these are simple machines that follow a given logic (Peñalvo & Ingelmo, 2023). However, GAI distinguishes itself through a more specific application. It is applied precisely to models with the unique capability to generate new, previously unseen information, reliant on the data on which they were trained. These models are beyond the limit of numerical forecasts or internal rules such like a calculator; instead, they venture into the realm of crafting fresh, human-like content that invites interaction and consumption (Peñalvo & Ingelmo, 2023).

Finally for this section, we would like to demonstrate the popularity of ChatGPT and how we believe we are witnessing the future. To do this, we will refer to this study (Peñalvo & Ingelmo, 2023), where a total of 3295 papers were retrieved: 1835 from Scopus and 1360 from Web of Science. After the elimination of duplications and other clarifications, they ended up with 631 papers (n=631). 422 out of these 631 papers mentioned that they have used Generative AI for content creation instead of other models, which lead us to understand a vast part of the AI technology is focused on G AI and utilizing it as their source for creation. Thus, we see the amount of individual work placed upon GAI is also increasing when we compare the # of papers written with the last year, there is a trendy increase. It can be assumed that we will be talking more about ChatGPT and GAI in the future.

As we move forward from the developmental history and how the AI evolved through which models and mechanisms, we will try to enlarge the background information a bit further by providing a sneak peek into the spectrum of applications and effects on the global landscape.

1.3 Applications Across Diverse Domains

GAI's implications span a multitude of domains and industries. It has far-reaching ramifications in medicine (Zhang et al., 2023; Zhou et al., 2023) where it aids in medical image generation and diagnosis, education (Khosravi et al., 2022; Vivar & Peñalvo, 2023) , enhancing personalized learning experiences, and art (Aguera & Arcas, 2017; Chatterjee, 2022) contributing to the creation of original artworks. Moreover, it has made its mark in music (Álvarez et al., 2023; Civit et al., 2022), marketing (Lies, 2022; Mikalef et al., 2023), software development (Kulkarni & Padmanabham, 2017 ; Mashkoor et al., 2022), and cybersecurity (Van der Zant et al., 2013).

Although the applications are vast and ever evolving, today AI developers most popularly choose to employ G AI to generate text, images, and videos. However, GAI also finds practical applications, such as Grammarly, a popular tool for enhancing English writing. This will be important later where we discuss the automative nature of some professions like translators. Regardless, many managers do their communication in English, therefore a tool that enables even intermediate level speakers to sound like professionals is an important note on how AI will affect the managerial behavior. As AI's potential to enhance our quality of life becomes evident, another example comes from medicine sector, investors are increasingly supporting its development in the biotech industry. Gartner—an American management consulting company—predicts that by 2025, 50% of drug discovery will involve AI since medical technology will be beneficial for pharmaceutical sectors. Moreover, some mental health apps are already testing ChatGPT, designed to provide users with answers to their questions (Mondal et al., 2023).

If we imagine a manager from an R&D department or a customer service agent for a textile firm, the transformative nature of GAI becomes more and more observable as the applications across occupations are expanding. An additional point of view of applications in real life comes from the essential unit in our houses, our kitchens, in this case GAI improves how we select ingredients for meals and prepare food. Imagine a chatbot that can access and present the most highly rated cooking tips found in the comments section of a recipe. This innovation would simplify the cooking process, making it more efficient, and encourage the sharing of culinary knowledge within the cooking community (Chui et al., 2023).

Stitch Fix, a company known for utilizing algorithms to recommend style choices to its customers, has ventured into the realm of DALL·E, a text-to-image generation model. They employ DALL·E to create visual representations of products tailored to individual customer preferences, encompassing aspects like color, fabric, and style. With this technology, the company's stylists can now transform a customer's textual description into a visual depiction of a clothing item. Subsequently, they can easily pinpoint a matching item from Stitch Fix's extensive inventory. This innovation enhances the personalization and efficiency of the shopping experience for Stitch Fix customers. (Chui et al., 2023)

Returning to managerial point of view, Generative AI systems could also create first drafts of circuit designs, architectural drawings, structural engineering designs, and thermal designs based on prompts that describe requirements for a product. Indicating that with the correct prompting, complex questions can be resolved via GAI. It is important to recall this part since we will build our hypothesis on how GAI can improve the complex work of managers. Chui et al., 2023) .We can create 3 basic subsections for GAI to understand how such help is occurring in our lives and consequently in working life. Our behaviors are changing mostly due to these skills of GAI.

To begin with, a change that GAI brings in our lives is *virtual assistants and information extraction*. Siri, Alexa, Google Bard, and many other virtual assistants are already taking place in our lives in one way or another. These virtual assistants are computer programs or applications that utilize AI to understand your questions or commands and help based on prompts. They function as digital helpers capable of scheduling appointments, answering questions, setting reminders, playing music, and performing various other tasks, all aimed at making our lives easier. They represent a shift in the capabilities of search engines, moving beyond basic search functions to multifunctional virtual assistants that can handle creative tasks, explain complex topics, and extract information from diverse sources (Aguilar, 2023).

We observe further impact in our lives specifically at customer service function, the change came with the emergence of the chatbots. A chatbot works as a computer program that can chat with the user. It uses technology to understand what has been said or typed and generate answers. It serves a robot friend on your computer or phone. Their use in customer service has created a significant due diligence process where many companies are deciding the amount of integration they need to do before they are behind regarding the technological evolution. Chatbots and customer service will be discussed in more detail in the upcoming chapters yet to briefly mention, ChatGPT-powered chatbots have proven highly effective in providing instant responses to customer queries and handling routine tasks, allowing human customer service agents to focus on more complex issues. Companies like H&M, Sephora, and Santander have embraced ChatGPT-powered chatbots to enhance the customer experience (Gao, 2019).

Multimodal Processing and Text-Audio Generation is another enabler of the technology in its way to finding real-life implications. It is an emerging field that fuses textual, acoustic, and visual information using cross-modal fusion and attentive pooling techniques (Liang et al., 2018) This innovation holds promise in various applications, including social media content generation. Text-music generation is another emerging area, where AI models correlate audio and lyrics (Yu et al., 2019).

To connect the discussion into managerial behaviors, **Table 1** is an attempt to predict the applications of GAI in different management fields. Here we see content creation, chatbots, planning, training, optimizing, digitalization, knowledge management via guidelines, automation of documents, presentations, motoring, and we see some strategical decision making especially in operational management. The reason why these predictions are hesitant to integrate or replace management with GAI is that, beside the problems that we will mention regarding the use of GAI, there are incompetencies of the technology in comparison to our complex decision-making system. We will build more on this later.

In conclusion, GAI's capabilities and implications are profound, touching numerous aspects of our lives and transforming industries.

1.4 Major Concerns Regarding the Use of GAI

To end this chapter, after we introduced its history and some of the implications that we observe, we should also be familiar with the fact that there are serious problems that come up with the emergence of GAI, to have a better understanding when we are discussing how it is affecting managers and employees in the upcoming sections. These problems will shed light on why some of the tasks are irreplaceable by GAI and crucial attention spots that need careful consideration in the event of GAI usage for a manager or a worker.

Factuality is a major concern regarding the products of GAI. ChatGPT acknowledges that it makes mistakes yet unless the user detects the mistake the flawed information stays present which can lead to problematic decisions if they are used by managers. One study conducted regarding the factuality of ChatGPT found that 80% of the responses generated were indeed not factual yet they are convincing and anyone without the professional expertise can be easily deceived (Brewster et al., 2023). On top of mistaken information, large models like ChatGPT do not update themselves every day yet the world we live in is constantly changing which will eventually lead into false and misleading information (Dilmegani, 2023). It should be remembered that harmful products of GAI can seriously damage one's reputation or a firm's credibility if published publicly as facts.

Factuality concerns are preventing GAI to be applied at major stakes due to their nature of intolerance for mistakes. Such examples will be healthcare (Reddy et al., 2020), machines with autonomy (Grigorescu et al., 2020) and science discovery (Cao et al., 2018; Gil et al., 2014).

These inaccurate outputs from the ChatGPT can lead to legal concerns which bring forth another problem, legal issues that comes with the usage of GAI. Legal problems find themselves a spot since they can create materials that can be used for crime, or it can unintentionally lead one to criminal action with the data that it provides (Budhwar et al., 2023). Possible criminal uses can include the following:

- Social manipulation and weakening ethics and goodwill. Maleficent users can advance as far as "social engineering" attacks where AI convinces users to provide secret information such like financial data. (Wach, 2023 ; Mondal et al., 2023)
- Widening socio-economic inequalities (Efe, 2022 ; Lutz, 2019; Kitsara, 2022 ; Kopalle et al., 2022 ; Zajko, 2022)
- Fake videos, texts, voice recordings or other materials to harm individuals, ideas, or organizations. *Deepfake* is an advanced form of creating these unreal materials. It is difficult to distinguish the real one from the fake ones which raises ethical questions (Dilmegani, 2023). It is also problematic regarding fake profiles of users to boost and manipulate views in online platforms (Mondal et al., 2023).

- The *fair use doctrine* which is a doctrine from the U.S. that regulates the ownership and right to use of copyrighted material without asking written permission from whom holds the rights is another consideration. With the AI, imitations of original work can easily be created (Marche, S. 2022) . Intellectual property, privacy and accountability are further considerations. (Budhwar et al., 2023)

Technostress is another crucial concept that managers and employees need to get familiar with. As the name indicates, such stress that comes from technological advancements can have performance related problems and it can affect the wellbeing of the organization.

One element of the technostress is whether the technology will create an overload on the worker, resulting in an excessive amount of work to be done (Sayed et al., 2022). Parallelly, AI brings a transformative effect with its use at jobs, and we can observe increased productivity for some occupations as it creates technostress for the user (Newman et al., 2022). Moreover, if such stress leads one into extra hours spent into learning the technology outside the working hours, it's estimated that the stress is accelerated by its presence for the users (Budhwar et al., 2023; Chen et al., 2022). The stress acceleration goes even further when we consider the amount of time invested in to stay competitive and to be able to provide the new basic requirements is possibly leading to reduced time spent with family or with hobbies and can be considered as an invasion of personal life (Wu et al., 2022). Furthermore, it will be observable for managers and employees that the complexity of the work will be overwhelming for some. As it will be harder and harder to cope and excel at the usage of technology it can lead to people avoiding the technology completely or lose their confidence at their work for the ones who couldn't figure out the integration of their work with AI (Hang et al., 2022 ; Dijmărescu et al., 2022 ; Wang & Zhao, 2023). The effects go even beyond this and lead to harmful consequences for organizations. If a worker or a manager feels that their job is under threat due to the other co-workers with techno skills, for example, knowledge sharing in the organization might be disrupted since the workers would like to preserve their knowledge and not to create leverages for others (Korzynski et al., 2021; Zhang et al., 2022).

Another consideration that a manager or worker should consider is the possibility of a detrimental problem where the information received from AI might generate biased outputs, reinforcement of stereotypes and dissemination of misinformation (Bender et al., 2021; Bommasani et al., 2021). These can cause potential hazards regarding the output of the user and if it is adopted widely without the necessary corrections, it can create long term negative effects on society as a whole (Cao et al., 2023; Dhamala et al., 2021; Kenton et al., 2021; Liang et al., 2021 ; Nadeem et al., 2020 ; Solaiman et al., 2019).

We are now familiar with the technological roadmap of GAI and how it became the thing we use today as well as we are introduced to its increasing popularity and tremendous domains in which it has been applied into and finally major concerns that come up with its output. We also know about some base activities that GAI can perform and are suitable for business functions such like chatbots and customer service. We will now expand our research and investigate the change it brings in a more specific manner especially at Labor market, managerial duties and how they change with GAI, as well as how different business functions are evolving in their daily tasks.

Chapter 2

Effects of GAI / AI on Labor Market, Industries, Professions, and Managerial Duties

As we covered the general background of AI, particularly GAI technologies, naturally the upcoming step will be the analysis and literature review of its effects at macro and micro level on professions. Although the aim of the paper is to discover the effects of GAI on managers, it is still valuable to dig deep into major changes since the cumulative information regarding the landscape of GAI and its integration will be useful to see the bigger picture.

We will cover observations and expectations regarding the labor market and discuss the economic benefits which will ease to see why managers are considering adapting GAI into their occupation. Finally, we will move into the changes regarding the main responsibilities of a manager and their transformation with GAI.

2.1 Literature Review of Expected Change that GAI will Bring into Labor Market

"Each time a machine learning (ML) system crosses the threshold where it becomes more cost-effective than humans on a task, profit-maximizing entrepreneurs and managers will increasingly seek to substitute machines for people" (Brynjolfsson & Mitchell, 2017)

The above quote elegantly describes the inevitable change. In the capitalist world where profit maximization is the main engine of the global economy, whenever we see a potential efficient upgrade at work, it is justified to expect that the upgrade will be adapted by organizations, such as in the event of GAI.

The effect of AI on the labor market is not completely black and white where it is easy to make comments regarding whether it is a good thing or not. We observe creation and destruction at the same time; therefore, GAI creates a dual effect. Some industries will benefit from increased automation that comes with adaptation of GAI, leading to enhanced productivity. Automation is the nature of the work where it has a high degree of repetition or requires less complex cognitive tasks, therefore the work can be handed out to machines. Further discussions regarding this topic are held in the further chapters. However, for others, this automation poses a threat to the workforce engaging in tasks that are highly automatable. This phenomenon is expected to result in both the streamlining of work processes and the displacement of workers in certain sectors (Zarifhonarvar, 2023).

At an initial glance, we see the estimations of labor market indicating a reduction regarding the need for workforce. The World Economic Forum's report on the future of retail indicated that automation could jeopardize "over 40% of consumer goods jobs and at least 20% of retail jobs in the next ten years" (World Economic Forum, 2017). Retail is a significant source of employment in many countries (McKinsey, 2017) as of in 2017. This research estimates that between 75 million and 375 million individuals may need to switch occupations due to automation threats. In the United States alone, up to 73 million jobs could be at risk, with a minimum of 39 million under threat. However, while these job losses are projected, it's also expected that 16 to 54 million new jobs will emerge. Consequently, employers will face the challenge of providing training for these new positions (Canals & Heukamp, 2020).

Furthermore, one study (Osborne & Frey, 2013) estimated that 702 jobs could be automated. As expected, automation is a reason for a reduction in need for workforce. We will explore the relationship between automation and workforce in the related section in the later parts of this paper. Regardless, to provide a broader perspective, comparable figures indicate a 47% employment risk in the US, 35% in Britain, and 49% in Japan (Frey, 2019). Notably, jobs that don't require high levels of specialization are more susceptible to automations. This concept is exclusively important since as we go through the literature by GAI's effects on jobs, we will observe a familiar pattern when we discuss its effect regarding managerial duties.

Contradictorily with the previous study, other studies predict of 97 million new job openings resulting from the introduction of Generative AI (Jetha et al., 2023). These new roles will involve tasks such as maintaining and managing Generative AI, including roles in prompt engineering, machine learning, and positions focused on ensuring transparency and reliability in AI systems. These are the occupations that are expected to arise soon as there will be natural demand for professional level GAI usage globally.

AI's impact will extend beyond job creation. According to one study (Mondal et al., 2023), logistics operations should harness AI to minimize their environmental footprint and mitigate industry-related damage. This is a vast concept that requires its own section to investigate but to remain intact with our topic, we will skip just by mentioning it, hoping that our perception will be broadened by the fact that in the future even environmental concerns will be addressed by GAI.

Returning the transformation of jobs, managers will observe these changes like trainings, job losses, new positions, and necessity for integration of GAI in everyday tasks specifically if their industry is under heavier exposure to GAI. This is important because the level of impact will be contingent on the level of exposure. Furthermore, as the specific capabilities of GAI for managerial purposes introduced before such like chatbots, some major players and managers are leveraging GAI for their benefit, negative results are also observed for some industries. The data about this will be present at the economics of GAI section.

To provide a more generic look on the industrial level effect, we will present this study (Eisfeldt et al., 2023) where sectoral level exposures are investigated. It will complete our understanding of high and low exposures of occupations, later, we will combine this with economics of the adoption of GAI and come up to conclusions.

Table 2

Major U.S. Firms with Highest and Lowest Exposure to GPT

Company Name	Generative AI exposure	MktCap	Sector
Panel A: Top 15 Large U.S. Companies with Highest Exposure to ChatGPT			
Int. Business Machines Corp	0.488	125	Information
Intuit Inc.	0.480	111	Information
QUALCOMM Inc.	0.479	132	Manufacturing
Fiserv Inc.	0.475	66	Information
NVIDIA Corporation	0.468	337	Manufacturing
S&P Global Inc	0.452	103	Admin. & Support Services
Broadcom Inc	0.449	195	Manufacturing
Verizon Communications Inc	0.444	157	Information
Microsoft Corp	0.442	1,700	Information
3M Co	0.442	69	Manufacturing
Advanced Micro Devices Inc	0.441	96	Manufacturing
ServiceNow Inc	0.434	85	Information
Adobe Inc	0.427	147	Information
PayPal Holdings Inc	0.418	96	Information
Thermo Fisher Scientific Inc	0.411	203	Manufacturing
Panel B: Bottom 15 Large U.S. Companies with Lowest Exposure to ChatGPT			
Company Name	Generative AI exposure	MktCap	Sector
Starbucks Corp	0.119	100	Accommodation & Food Svcs
McDonald's Corp	0.194	201	Accommodation & Food Svcs
Dollar General Corporation	0.212	57	Retail Trade
Target Corp	0.235	76	Retail Trade
Walmart Inc	0.235	385	Retail Trade
Lowe's Cos Inc	0.238	120	Retail Trade
TJX Companies Inc	0.243	83	Retail Trade
Costco Wholesale Corp	0.252	221	Retail Trade
Union Pacific Corp	0.253	121	Transportation & Warehousing
CSX Corp	0.256	61	Transportation & Warehousing
United Parcel Service Inc	0.256	123	Transportation & Warehousing
Home Depot Inc	0.261	303	Retail Trade
Tesla Inc	0.283	719	Manufacturing
Northrop Grumman Corp	0.291	83	Manufacturing
Mondelez International Inc	0.292	85	Manufacturing

Note that the lowest score category only shows a subset of a larger set of occupations with zero Generative AI exposure.

Source: "Generative AI and Firm Values," by Eisfeldt et al., 2023. p. 46 (https://www.nber.org/papers/w31222). 46NBER Working Paper No. 31222 JEL No. E0,G0

Now let's shift our focus to occupational level exposure. **Table 3** is a demonstration of the same study (Eisfeldt et al., 2023) where researchers investigated the top 20 occupations and their respective exposure rate. One important note is that such professions like Telemarketers, Translators, Computer Programmers are all subject to leave portion of their workload into Generative AI, therefore, as mentioned earlier humans will be subject to being replaced by machines where it is possible (Brynjolfsson & Mitchell, 2017). On the other hand, low exposure tasks might be subject to expose in the future, when GAI is implemented into actual robots and when these robots are feasible to acquire, but until then, a tailor's work cannot be imitated or aided by GAI, the tools are simply not adequate to replace a master at their craft at this moment.

Table 3

Highest and Lowest Generative AI Exposure Score Occupations

SOC Code	Occupation Title	Exposure Score
41-9041	Telemarketers	.96
43-9081	Proofreaders and copy markers	.95
43-3031	Bookkeeping, accounting, and auditing clerks	.87
15-2021	Mathematicians	.86
15-1251	Computer programmers	.85
43-9022	Word processors and typists	.85
43-3011	Bill and account collectors	.83
27-3091	Interpreters and translators	.82
43-9111	Statistical assistants	.82
15-1254	Web developers	.81
43-6011	Executive secretaries and executive administrative assistants	.77
43-3051	Payroll and timekeeping clerks	.77
43-6014	Secretaries and administrative assistants, except legal, medical, and executive	.77
43-5061	Production, planning, and expediting clerks	.76
15-1212	Information security analysts	.75
43-6013	Medical secretaries and administrative assistants	.75
27-3043	Writers and authors	.75
43-4021	Correspondence clerks	.74
43-9061	Office clerks, general	.74
41-3091	Sales representatives of services, except advertising, insurance, financial services, and travel	.73
⋮	⋮	⋮
39-5093	Shampooers	0
51-6041	Shoe and leather workers and repairers	0
51-6042	Shoe machine operators and tenders	0
51-3023	Slaughterers and meat packers	0
47-2022	Stonemasons	0
47-2221	Structural iron and steel workers	0
51-2041	Structural metal fabricators and fitters	0
29-9093	Surgical assistants	0
51-6052	Tailors, dressmakers, and custom sewers	0
47-2082	Tapers	0
49-9052	Telecommunications line installers and repairers	0
47-2053	Terrazzo workers and finishers	0
51-6064	Textile winding, twisting, and drawing out machine setters, operators, and tenders	0
47-2044	Tile and stone setters	0
51-9197	Tire builders	0
49-3093	Tire repairers and changers	0
51-4194	Tool grinders, filers, and sharpeners	0
39-3031	Ushers, lobby attendants, and ticket takers	0
49-9064	Watch and clock repairers	0
53-7073	Wellhead pumpers	0

Source: "Generative AI and Firm Values," by Eisfeldt et al., 2023. p. 64 (https://www.nber.org/papers/w31222). 46NBER Working Paper No. 31222 JEL No. E0,G0

Consequently of both tables, we can start discussing that IT firms like Intuit and IBM are leading the exposure with their applicable nature and easy integration possibility with GAI, manufacturing firms such like 3M and financial authorities such as Standard & Poor are also adapting GAI into their business modal in one way or another. Largest U.S. firms which placed at the bottom of the list not surprisingly include restaurants such as Starbucks and McDonald's, since most of the work remains at *no effect by GAI* in comparison with other industries. Restaurants are followed by retail firms and transportation giants such as UPS and Walmart, again their workforce is consistent with drivers and retail workers where GAI simply can't automate any activity at this point. One keynote here is, we previously mentioned that retail sector will be a subject to major changes with the AI, however at this point the exposure remains low.

Theoretically, with the upcoming changes, stores can function with less and less amount of labor and more with machinery. These companies have employees that are less exposed to the GAI compared to the top percentile, a truck driver is still a non-autonomous work by its nature that can't be substituted by GAI is the conclusion for us after analyzing **Table 2** and **Table 3**. We will be watching for upcoming changes regarding Tesla's innovations with driverless trucks and how they will be implemented in the world of transportation in the future. Let's take a comprehensive look at industrial level exposure and observe the low exposure score of transportation, as an example.

Table 4

Generative AI Exposure Scores by Industry

NAICS Code	Industry Title	Exposure Score
52	Finance and insurance	.49
54	Professional, scientific, and technical services	.49
55	Management of companies and enterprises	.48
51	Information	.47
42	Wholesale trade	.35
91	Federal government	.34
53	Real estate and rental and leasing	.33
90	Government	.3
22	Utilities	.29
61	Educational services; state, local, and private	.29
56	Administrative and support and waste management and remediation services	.27
81	Other services (except public administration)	.24
31-33	Manufacturing	.24
44-45	Retail trade	.22
62	Healthcare and social assistance	.22
71	Arts, entertainment, and recreation	.22
21	Mining, quarrying, and oil and gas extraction	.21
48-49	Transportation and warehousing	.2
23	Construction	.17
72	Accommodation and food services	.11
11	Agriculture, forestry, fishing and hunting	.086

Source: "Generative AI and Firm Values," by Eisfeldt et al., 2023. p. 65

(https://www.nber.org/papers/w31222). 46NBER Working Paper No. 31222 JEL No. E0,G0

A further note comes when we investigate the wage distribution and impact of ChatGPT across industries. *The findings imply that "technological advances impact workers at the higher end of the wage distribution" (Kogan et al., 2019).* Moreover, *"high share of non-routine cognitive analytical tasks or routine cognitive tasks"* are by nature the most effected occupational responsibilities yet manual physical tasks are relatively unaffected (Chiui et al., 2022). Building on this, considering a manager where tasks are highly cognitive and for some parts of it tasks are routine, it is expected that duties of managers are subject to major changes. The tasks that lie in between routine and cognitive can be exemplified as reporting and organizing regular meetings.

There are many more accelerating impacts of GAI, but as expected, its effect is rather weak for some jobs. Some industries and occupations are expected to remain relatively unchanged due to the requirement for high levels of autonomous decision-making and the unpredictable nature of their work. Professions such as nursing aides, janitors, food service, and roles that demand strategic leadership responsibilities, such as C-Suites in large corporations, are expected to be less susceptible to total AI dominance (Brynjolfsson & Mitchell, 2017). That being said, managerial life and work are subject to relatively minor changes when cognitive necessity of the work increases. In fact, automation is a key concept that defines whether the magnitude of the effect will be major or relatively minor.

To tighten the broad discussion on GAI's effect on labor market, now we will delve into more managerial responsibilities which find place in business functions. We will look at it in a deeper way, and to do so, we will use a categorization based on work by McKinsey Digital Blue (2023) which examined the anticipated impact of GAI. This research provides valuable insights into the touchpoints of GAI, offering predictions and observations on the impending changes. It also serves as a summarization of the foundational information we have been conveying regarding the transforming touchpoints of managerial behavior.

Customer Operations: Call centers will undergo massive transformation with Chatbots and smart customer service agents.

Software Development: Coding, testing, designing, maintenance of programs, ERP and other internal tools will be affected by GAI.

Product R&D: Market and academic research, ideation, simulations for early product development, prototyping and testing will get effected by GAI.

Legal, Risk, and Compliance: Contract creation, litigation support, risk allocation and management will be aided by GAI.

Marketing and Sales: Market research, creating marketing strategy, interaction support, pricing, item matching, etc.

IT: Activities related to internal information systems, help desk,

Talent and Organization: Organizational performance tracking, talent management, recruiting, monitoring, learning and development, human resources.

Finance and Strategy: General accounting, financial planning and analysis, account management, market intelligence, strategic planning.

Therefore, we are concluding that managers and workers will realize such changes as well as they will realize a change in the decision-making process. It can be assumed every part of business functions are subject to change. We observe this phenomenon because in each department, managerial duties involve some sort of similar activities like decision making, planning, etc. This will create the base for our definition of managerial duties to address changes when we are discussing the transformation regarding the managerial behavior in the upcoming chapters.

Before we examine the economic value of GAI and move on to managerial behavior, we will stress how employees and their functional duties are changing by addressing the professions where we see the change is at its peak.

2.2 Changes in Employee Behaviors – Occupations where the Change is at its Peak

Employees, the main element of any organization, the structural necessity. Employees are also undergoing many changes, a lot of progress and replacement that are happening for industries, businesses and managers are also directly affecting them too. Employees are experiencing technostress as much as managers. Changes in labor market affects their well-being since as some of them progress, some fails to do so. We see many automative tasks are being replaced by GAI or if not, it is becoming a part of regular daily work. To see the picture and the magnitude of change at a better perspective though we will discover two related business functions which are marketing and customer service. We choose these functions since the exposure to GAI is at one of the highest compared to the others.

Customer Service had gone under drastic changes with GAI. First thing to be discussed is that, as these intellectual machines such like chatbots are present and available for marketers, they can be used for “engagement with humans” with the pre-provided information to the bot and they can serve as a customer service agent while generating responses and even answer FAQ’s (Canals & Heukamp, 2020).

Four key complementary elements in which GAI can integrate with the Customer Service Industry starts with Resolution during initial contact. Anyone called a flight company already experienced this phenomenon. As you provide a little information, the GAI system pulls the data from the database for each customer, and it enables the representative to be more efficient and effective since issue resolution is simplified with GAI. Research that digs deeper into this concept with five thousand customer agents realized after the integration of GAI, the issue resolution increased nearly 15% per hour while the total effort observed a reduction by 9% (Chui et al., 2023).

The second operational improvement comes from Customer Self-Service. Chatbots can provide complex answers to customer’s issues in every language and without geographical constraints. This enables the bot to serve as a human agent and successfully undergo customer inquiries. One suggestion (Chui et al., 2023) takes account of 50% reduction of workforce especially for the banking, telecommunication and utilities sectors since their operations are already being replaced by GAI, in fact, half of the communications are already being handled by machines depending on the firm’s adoption of GAI. Their research indicated that for the company with five thousand agents, there is a 25 percent improvement at demand for attrition of agents and requests for speaking with managers.

The third way for assistance is reducing response time. GAI can also provide the same protocol that will be given by the operator, which enables time savings. However, it is trickier than it sounds. Since the skillset of GAI is pre-determined, while it increases the low-skill customer agents by providing higher levels of service, for some cases it reduced the effectiveness of the agent when the agent is high-skilled. This concept is present for various industries, as AI reduce the skill gap between workers, low-skilled workers have the potential to imitate and perform better and catch up with high skill workers with the help of GAI.

We provided that the skillset of GPT includes substantial efficiency regarding text, sound and image generation and it imitates human like conversations. In addition, we will consider how some of the professions like telemarketing are at the highest level of exposure to GAI since these areas are at the peak of exposure.

A customer service employee now experiencing a change in nearly all the tasks that they do, they provide answers with GAI, they handle solutions with GAI, they contact customers via GAI etc., which lights up the way to believe that professions that are highly exposed to GAI and when the nature of the work is carries a subsidiary effect, we are witnessing a total transformation of occupations where every task is integrated or being replaced with machines and the need for human labor is less and less important. A concluding note to conceptualize the change can be summarized as the following : When we build good relationships with customers it increases their satisfaction therefore loyalty, in addition, as they enter these relational exchanges with firms when they believe that the benefits derived from such relational exchanges exceed the costs. Generative AI is an excellent tool to help strengthen relationships with customers with its capabilities and provide an overall positive experience (Berry & Parasuraman, 1991; Hunt et al., 2006).

We would like to extend this section by providing further transformation examples regarding managerial responsibilities at Human Resources Department where we observe important changes. One task related to performance management is performance reviews based on the previously determined Key Performance Indicators *(KPI)*. Remembering that GAI answers upon trained data, if the training is done by experts regarding specific expert knowledge, it can accomplish meaningful assessments. One example comes from Confirm, (Parisi, 2023) the company reported that their trials for a performance review system has been successful when the KPI'S are prepared by colleagues of the ratee. This indicates that, if GAI is trained by professionals of a specific duty, in this case the colleagues, it can measure the correct KPI's and measuring performance of the employees with this method has proved success. Managers who are at the monitoring and screening stage now will start to take the help of GAI to standardize the processes instead of having them done individually. This argument is supported by the *Scientific Management Theory* (Taylor, 1919), where he discusses that as the standardization increases organizational productivity may be increased. This is the KPI for all the managers since they must be actively searching for the ways of increasing productivity regarding their area of impact. We will use this argument at building managerial responsibility model.

However, meanwhile managers are transforming their behaviors and adapting the latest tech in their profession, one major consideration came from the CEO of Confirm, the firm that conducted the experiment, stated that there is also a downside. According to the CEO, performance management is a human process and GAI, specifically ChatGPT has not yet reached enough excellence to perform such activities, indicating that if managers adapt into the technology and use them in their daily tasks, it must not be a total handover of the tasks but instead it must be supervised by a human controller which is a manager in this case to avoid inequal and unjust decisions. Considerations goes further with another problem; the pragmatist nature of humans prevents managers to make necessary arrangements and complete their tasks with GAI. When interacting with a chatbot humans have a tendency to engage in unethical behaviors (Kim et al., 2022), which will prevent correct assessments and therefore the total replacement of the managers regarding performance management via GAI. (Budhwar et al., 2023; Varma et al., 2022). The interpretation of Confirm opens room to discuss whether GAI will have a domination of replacing responsibilities or should be handled carefully with managers. Keeping this in mind, the issue will be addressed in the managerial transformation section.

Following performance management, another responsibility within functional level of a manager is recruitment and job matching. As mentioned before, managers will integrate their tasks with GAI when possible since it is profitable and increases productivity within the firm therefore managerial behavior is also subject to change when this task is performed. Not all aspects of the work will be changed for a manager, but regarding recruitment, with the digital age, it is a common knowledge that recruiters receive excessive number of applications especially for popular positions and AI has made its impact already and changed the way managers operate with its high computing capabilities (Silva et al., 2020). For a single person it is not feasible to carefully analyze, compare and conclude the perfect candidates amongst thousands of applicants since it is vastly time consuming, yet with given filters and prompts, AI proved itself to be successful.

E-HRM created an overwhelming task load and technological advancements provided the solution for the problem that it created. AI tools now can screen, summarize, and do the matching for job and candidate. Further applications are regarding the live monitoring of the candidates during the interview and micro-monitoring to detect *hidden and basic attitudes* which is a tremendous help for a recruitment manager and opens the way for them to make much more educated conclusions (Budhwar et al., 2023; Black & van Esch, 2020; Korzynski et al., 2023). Additionally, performance management and screening withing the company via GAI also leads managers to track the talent pipeline within the company since its an essential duty to promote and degrade people regarding their performances. AI can track individuals and hold record. It is important to note that talent management within the company is favorable since employees already has a familiarity with the company and orientation is not necessary as well as their recognition for internal procedures (Korzynski et al., 2023).

Managers, specifically functional managers like HR Managers, find further changes in their behavior in their work. Tasks that are subject to automation will be assigned to AI in time as managers learn more about how to efficiently use this technology. Such tasks also include job descriptions, resumes and HR guidelines, as well as internal horizontal and vertical communication (Pavlik, 2023). It can dictate improved job satisfaction since it makes the procedures easier with its tools and it doesn't aim to replace human interaction but instead create the proper base for interaction to take off as long as humans develop their trust in AI and procedures it brings. An employee that can reach out to its higher rank supervisors without needing to contact them in person is particularly good for employees that are suffering from social anxiety (Votto et al., 2021 ; Eubanks, 2022 ; Korzynski et al., 2023).

What we need to highlight in here is that, after these discussions, it is easy to observe that AI, and in particular GAI, is a valuable tool for operational efficiency. Managers are going through a change in their duties since some of the duties can be performed by GAI yet since there are still considerations regarding its human-like capabilities when interacting with humans it's still a complementary tool for managers instead of an authority to perform tasks.

To conclude, we can summarize that for a worker, especially working in the areas where GAI has seen substantial capabilities, their way of completing tasks is evolving. However, there is still more to cover. We examined the expected change in different functions and responsibilities but just because GAI can help the workforce in their duties, it doesn't automatically indicate that the technology must be adapted. The integration is justified in customer service and marketing domain where efficiency increase is proven, However, we would like to understand more whether such positive impact is present across all the industries. To underline the incentives of the adaptation of GAI into managerial behavior, we will look at its economics in the following section and we hope that it will help us to realize the reasoning behind adaptation and magnitude of it. Therefore, we will discuss why such change is inevitable. The spoiler is already given, it is profitable.

2.3 Economics of Early Adoption of GAI Across Industries

Recalling the study done by McKinsey as we referred before, same study provides further insights **(see Table 5)** in the top industries aiming to understand whether deploying GAI in some use creates a value. We will use this research to begin with to see whether using GAI generates a monetary return.

85-billion-dollar prediction solely from 3 industries indicates the magnitude of the innovation. It is already clear that GAI is the "next big thing" that contains enormous value when adapted. As this being a generic look, we will provide further research conducted to understand specific contribution potential of GAI at a deeper level, in particular ,on the daily revenue generation.

Moreover, following study is enlightening to grasp the early economic effects of GAI. Eisfeldt et al (2023) found that there is an effect in exposure to GAI and daily revenues. They noted that:

> *We measure firm-level exposure to Generative AI in two steps. First, we use ChatGPT itself to assess whether each of the 19,265 tasks currently performed by various occupations can be done by the current ChatGPT or by future ChatGPT after investment in additional capabilities (Eloundou et al. 2023). Then, we aggregate the task-level exposure measures to the occupations in the O*NET database. We have conducted a comprehensive analysis involving 2,518 publicly traded companies in the United States, focusing on the extent to which their workforce is exposed to Generative AI. Our approach involves creating portfolios known as 'Artificial Minus Human' (AMH), where we take long positions in companies with greater exposure and short positions in those with lesser exposure to Generative AI. Our findings reveal that companies with higher exposure to Generative AI generated daily excess returns that were 0.4% higher than those of companies with lower exposure, particularly after the release of ChatGPT.* (p. 2)

The findings are summarized as:

- Companies that can replace their workforce with cost-effective Generative AI-driven technology will increase their free cash flows by reducing expenditure on human labor.
- Companies whose employees' skills complement Generative AI technology will see improved cash flows because of technological advancements that enhance the effectiveness of their workforce.

Eisfeldt et al. (2023) suggests that as they measured the firms and their exposure with GAI, they found that:

> *Cumulative returns to holding the AMH portfolio that is long the highest-exposure quintile, and short the lowest-exposure quintile from the released date through March 31, 2023, are over 9%.* (p. 4)

From this standpoint, we can conclude that, there is indeed value lies underneath the adoption of Generative AI across industries and we can expect to see an increase in its adaptation in the upcoming years. Managers are adapting this advancement since we live in a world where profit maximization is still relevant and GAI is a new section of productivity, therefore, profitability.

Moving on, although we have mentioned some industries enjoys the release of GAI by positive excessive returns and for some the case is rather inactive, not surprisingly, for some, the adaption ends up with unpleasant outcomes. The study justifies this argument by measuring returns and exposures. As we investigate the study a bit further, we come to the realization of the economic effects of GAI is not black and white. To support this argument, in following industries (see Eisfeldt et al., 2023) firms who are exposed to GAI had significantly better returns than to the firms with lower exposures.

- Manufacturing
- Administrative support,
- Waste management
- Remediation services industry

Yet, following grouping is the industries where firms with higher exposure leads to significant underperformance compared to the companies with lower exposure.

- Rental
- Leasing
- Real estate industry

This is very insightful since it gives us some fruit for thought; why do we see a reduction in revenues regarding these industries? We hypothesize that, GAI has many issues to be considered as an authority and has further drawbacks when the nature of the work consists of rather interpersonal complex problems. In these industries customers look for credibility, trust, understanding and many more humane qualifications which also creates the performance difference between the occupants of these professions. A rental chat-bot is more likely to underperform a rental task since it lacks persuasion capabilities and can mostly perform as an information provider. However, these professionals are enjoying their expertise when performing their occupation. Such considerations bring us to the next topic to understand that the duties which are subject to major changes regarding managerial duties as well as duties that are likely to be remain same. In the following part, we will explore the reasoning behind why for some industries the exposure increases the returns whereas for the others its exposure can backfire by reducing revenues and whether our hypothesis is correct.

2.4 Reasoning for the Performance Difference of GAI Exposure Across Industries

As we have gained an understanding of how AI can both create and eliminate job opportunities, its economic impact regarding economics and exposure to GAI for various industries, and after we have looked at how some of the professionals are taking advantage of such innovation in various industries, it is now crucial to delve into the types of occupations most vulnerable to these changes to understand the magnitude of change in managerial behavior. If business functions are to stay unchanged, we can conclude that GAI will be ineffective, yet if we see businesses and functions are evolving, we will conclude that the future will look different with the introduction of GAI. It will also enlighten the way for us to understand why we are observing the vulnerability for some professions. *What could be the underlying mechanism?* To achieve an estimation for specific industries, we must consider the nature of various jobs and their interaction with Generative AI. This exploration will involve drawing insights from relevant literature to answer key questions regarding the impact of AI on different occupations.

There are three possible scenarios in which we can range the *nature of the work* and its relevance with GAI. These are *"no effect," "complementary"* and *"subsidiary"*. The literature suggests that the occupation that requires routine and autonomous work is most likely to be substituted by computers and respective autonomation it brings, however, if work requires other necessities and is non-routine, involves strategic decision making and problem solving, it's expected that the GAI will be present as a complementary tool for the worker, in our context, for the manager (Autor et al., 2003). It can also be assumed that if a work's nature consists of complex cognitive tasks, automating it via GAI will reduce the performance of the worker and firm, however, when used as a complementary tool it would have a positive impact, same with if the work is rather in a subsidiary position such like consumer service or content creation etc., automation would be beneficial.

We support our assumption primarily by *Transaction Cost Theory* (Williamson, 1981). Williamson discussed that, technology and transaction costs have an inverse relationship, indicating that as technological innovation increases; it's expected that transaction costs will decrease, such as communication and planning. As we discussed before, GAI proves itself to be extremely effective in fields of content creation, text, and audio generation etc., therefore we expect that if such transaction costs decrease with the integration of GAI, automatically the exposure will prove itself to be profitable and we will observe major changes regarding the managers and workers in such fields. This is not a brand-new issue to cover as well. With AI become more and more popular, it is the latest phenomenon regarding how technological changes are affecting worker's and management's duties, to be more specific, it was already an ongoing debate back in 1980's that whether the technological advances will bring an end to the managerial necessity in firms since technology is enabling the information flow within the organization and doing it more efficiently than before (Korzynski et al., 2023).

Therefore, if a worker is affected by GAI directly, the level of the effect will be the determinant to understand whether the worker will highly or slightly get effected. Two touchpoints appear to be resolved at this stage which is whether the GAI is serving as a complementary or subsidiary aligning with what has been mentioned before since "no effect" has nothing to do with our discussion. If the production can easily be replaced, imitated, or even improved by the GAI, then the worker will have more time to focus on other tasks or he/she can be assigned to a different role, however, the requirement to employee that worker significantly loosens (Noy & Zhang, 2023).

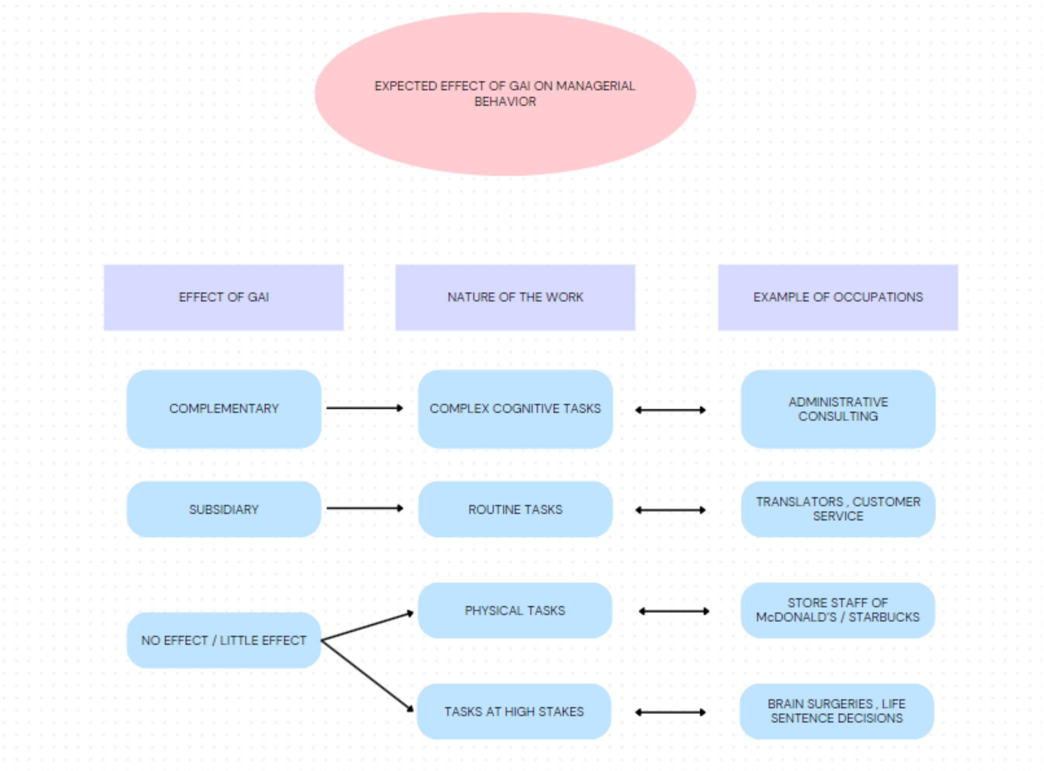
With a further look, considering general writing capabilities of a low-skill employee can now become significantly faster therefore it can be said that ChatGPT replaces the total effort of a worker instead of their respective skill level, which makes the innovation a balancing tool for different skill levels for all the users since the same-level material is produced by GAI regardless of the capabilities of the worker. However, the worker's abilities might thrive with the combination, for instance like in the case of an imaginary worker who educates herself to learn AI prompting and generates astonishing results. This creates a situation where worker's effort on the tasks at a large scale is subject to substitutions. This happens due to the enhanced skills with cooperation of GAI and worker, which will inevitably lead to even more capitalized / productive workers. In conclusion, we are observing a reduction for the demand of workers where automation is efficient as well as workers with higher demands since their efficiency is improved and they can perform more tasks at a better-quality level. This means some workers will be able to do more, and they will require to be compensated better. An example of this performance increase is that if the GAI will provide a draft for the worker who regularly publishes material to edit, the worker no longer needs to create the draft and lose time. Parallelly, if GAI creates ideas for the worker, brainstorming will be less time consuming for worker and this will hasten the task on hand to complete, in fact, in a brainstorming process, GAI can potentially highlight critical points which could be overlooked by the worker. Regardless, we are facing with an enhanced output (Noy & Zhang, 2023).

Therefore, we can conclude from the example of a worker whose work is improved with GAI when GAI serves as a complementary assistant, and it creates the environment where human and machine co-operates, the efficiency and the quality of the output possibly increases for some industries.

Before we move on to the possibility of backfires of these integrations, another aspect that we must consider understanding whether the change in managerial behavior is subject to preventions, we would like to fresh our minds regarding our discussion above. Our hypothesis is visualized at **Figure 1.** Note that we will build on this conceptualization more in Chapter 3.

Figure 1

Expected Effect of GAI on Managerial Behavior



Source: Author's Perception

With all that mentioned that comes from the introduction of GAI into the workplace, criticisms born considering that what happens if we observe a world where GAI is mostly integrated in the workforce and many products that we receive from companies are created or co-created by the technology. Before moving on to the managerial changes, last thing to keep in mind that beside the problems that has been introduced in the Chapter 1, there will be another consideration for firms that they must keep an eye on.

The assumptions come from Canals, (2020) where they argue that if the autonomous work is replaced or complemented by GAI and also if the industry is also responsive for such change by being available to substitute human workforce with GAI, there will be positive returns since GAI is better at some tasks than humans and there will be an surplus of time for workers because of the reduction at necessary efforts to complete some tasks which can be used in other responsibilities, ending up with the increasing the efficiency and profitability of the firm. This is the same argument that we had regarding the effect of GAI on the workforce. Many companies from various sizes are adapting to this technology or they are at the due diligence state where they are finding a way to start the adaptation since common sense is that this is the future to catch. However, it must not be forgotten that the technology is present and available for all the firms, and this creates a major problem.

Imagine many of the finance and investment companies use the same technology to create portfolios. What we would observe is all the firms will slowly become more similar as they rely on the technology and differentiation between firms and their products will not surprisingly reduce. A manager should always consider that, lets imagine a portfolio managers' duties as an example, is still creating tailored and unique work and create returns higher than the market average. If we would get similar portfolios from investment firms, their differentiated identity is subject to hazards. We find use of exact quotation from Canals, (2020) at this point since its their argument and explains the situation elegantly.

> *The fund management industry, for example, increasingly uses "robot-advisors" to make investment choices for their clients, but competitors all have similar algorithms for making their trading decisions, they will inevitably end up with very similar investment return.* (p 26)

Therefore, regarding industries where GAI becomes a strategic advisor, similarity of advice is a potential threat for the manager to be carefully evaluated. Inevitably, we conclude that using GAI even as a complementary tool might be tricky and adaptation on a larger scale, including handing over the strategical decision-making authority, does not seem to be an excellent strategy for firms and managers. Instead, we agree with their conclusion. Birkinshaw & Ridderstråle, (2017) and Canals, (2020) note that:

> *The imperatives for firms that are seeking to capitalize on the opportunities in today's fast-changing world involve acting on opportunities more quickly and being prepared to follow an intuitive or experience-based point of view, rather than relying heavily on empirical support.* (p. 27-28)

The bottom line is that it's better for AI to be used in the simple tasks and contracts to make the business more efficient and streamlined but any attempt of adopting it as a decision-maker will quickly result in imitation from competitors and being less distinctive (Canals, 2020). Managers will be better off if they balance the aid they will get from GAI and with this precaution they can avoid issues that are surrounding the use of GAI.

Before we end this chapter, we would like to stress further the "complementary" nature of the work -and to build more on an imaginary worker example where the worker enhances her ability to produce better outputs with collaborating with GAI - and its applications in management domain. We believe that it will complete the understanding when we refer GAI as a co-worker for management for some tasks.

Starting from algorithmic judgements we see a better performance and more accurate judgements from GAI then managers in many fields such like wine prices, cancer diagnosis and route selection (McAfee & Brynjolfsson 2017). Beside the fact that GAI can outperform managers regarding making predictions, it also helps them to improve their decisions in various business functions such as such as manufacturing, purchasing, sales, marketing, finance, or logistics (Agrawal et al. 2018). Manufacturing and operations managers are making better decisions especially at procurement since GAI helps them with historical data, demand and supply, quality, reliability via online presence and trust scores, it also tracks the data of inventory (Sanders, 2016). The managers who can gather all these information have a better chance to generate a bigger understanding of the entirety of the work. It enhances finance managers abilities have better decisions by providing tools and rich information regarding portfolio management via historical prices, yields, companies' performance, interest rates and the economic cycle (Canals, 2020).

Banks and consulting firms utilize the computing power to generate numerous scenarios and they dig deep into synergies (Canals, 2020). Negotiators are enjoying the technology by improving their research and *"claim formulation and other preparations"* (Budhwar et al., 2023) GAI helps negotiators by analyzing and providing arguments, it is excellent at generating speeches which are the responsibilities for negotiators. In addition, negotiators could use the ChatGPT-like innovations to help them research cases more widely and quickly than they could otherwise, for instance, to find and assemble precedents, develop arguments, and draft speeches. Moreover, union leaders and officials can draw on these innovations to facilitate the recruitment and retention of members, and communications with them.

It's good to recall that in customer service chatbots are answering FAQ's (Frequently Asked Questions) and in marketing it makes predictions about consumers (Canals, 2020). For managers who already have integrated data clustering into their work are using GAI to have estimations. In short, the domain of capabilities expands into patterns that are not easy to detect by managers, such as behaviors of consumers, dynamics of price and compute demand elasticity.

A final reminder is that all these changes and co-working with AI is happening because now the amount of data that algorithms feed upon are richer than ever and it enables them to compute advanced predictions. We believe the examples and application surface will be stretched further in time and we will observe new changes regarding managerial behaviors as these capabilities of AI proves its usefulness in other managerial tasks.

The next step is to investigate the pre-defined nature of work categorization and creating a modal for managerial behavior and connecting these to come up with an argument. We would like to form hypotheses on this matter to see if responsibilities of managers across different hierarchies and functions share autonomous and non-autonomous characteristics, therefore, we will be able to see the partial revolution of managerial behavior regardless of the function.

Chapter 3

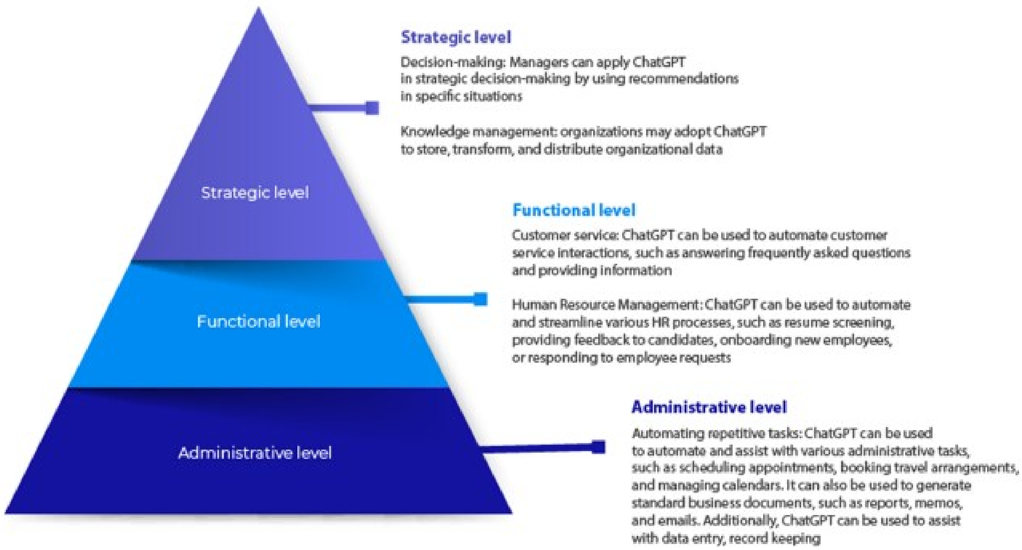
Managerial responsibilities, their evolution with GAI and managerial duty classification

There are plenty of discussion that have happened in the literature aiming to come up with a formula that describes the essential responsibilities of a manager. Although each manager's area of responsibility changes in daily tasks, the essence of their employment revolves around similar responsibilities, and we will consider two classifications regarding their work to understand how each responsibility cluster is changing with GAI. The aim to do this is to create a modal of managerial responsibility in a way that defines the managerial duties across managers from all functions and throughout the level of hierarchy between managers. The first approach will be the hierarchy pyramid and the latter part is a combination of multiple managerial task theories from the literature.

We start with the holistic approach that classifies the duties in a pyramid framework. The assigned duties are *strategic, functional, and administrative* duties (Korzynski et al., 2023).

Figure 2

Potential Application of Generative AI in Organizations



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Source : "Generative artificial intelligence as a new context for management theories: analysis of ChatGPT," Korzynski et al., 2023, *Central European Management Journal* 31*(1)* p. 3-13 (DOI 10.1108/CEMJ-02-2023-0091) © Pawel Korzynski, Grzegorz Mazurek, Andreas Altmann, Joanna Ejdys, Ruta Kazlauskaite, Joanna Paliszkiewicz, Krzysztof Wach and Ewa Ziemba.

Strategic level is where executives form their strategical decisions and lead the company, this is the level where a manager makes significant decisions that will lead the way for all the other operations. At this level, managers work with the complementary tools such like AI in particular GAI to obtain suggestions, study case studies, and form strategical recommendations. GAI helps with analyzing market trends, gathering competitive intelligence, and identifying strategic opportunities. Executives are also responsible with knowledge management where GAI is used to distribute, store, and manage the organizational information flow. An example will be the sharing of common organizational knowledge with distribution in forms of handbooks (Newman et al., 2022). We can consider a real-life example of Apple's introduction of Iphone's in smartphone market, the strategic decision was after carefully evaluating the market, technology, landscape and many other parameters, the company decided to move beyond computers and Apple.inc took a massive step towards becoming the giant as we know today. That is a clear example of a decision that has been made by a manager at a strategic level in the hierarchy.

Functional level is where managers perform their occupational tasks. For example, for a Finance Manager, investment management and portfolio analysis combined with tracking profit and loss can be defined as functional level duties. For a sales manager hitting monthly quotas is another example while for a production manager reaching out the necessary amount of output can be exemplified. To have a final deeper look at this function, if we were to examine a Legal Manager from Law Department, we would be listing his functional level responsibilities as:

- Risk Assessment and Mitigation
- Litigation Management
- Intellectual Property Management
- Legal Compliance
- Contract Drafting and Review

Administrative level is the coordinating base where to perform all the prior activities, some necessary activities should have been already done, such like record keeping and scheduling meetings but not only limited with these. At this point, the manager goes above and beyond individual or departmental responsibilities and must encompass a comprehensive understanding of different functions since coordination is an essential part of this level. Creating policies and procedures, best practices, guidelines and aligning organizational goals, resource allocations and interdepartmental collaborations are all examples of the duties of a manager with administrative level responsibilities. We can consider this as where a manager creates synergy between different functions and aims at improvements in efficiency.

We can exemplify these duties with real life tasks: such like, collaboration between departments can be maintained with cross-functional workshops or training sessions. For resource management, an administrative level management keeps an eye on all the functions in which he is supervising and allocating the resources accordingly between functions in an imaginary cross-functional project. We can also consider a communication platform where cross-functional communication finds place and it creates synergy between departments.

To compare these levels between each other, it can be said that they are distributed into different managers at different levels in the hierarchy. They have different scope and focus regarding their aim, yet they are all crucial for organizations, distinctively contributing at organizational objectives.

We expect to observe changes in each level; therefore, we hypothesize that GAI will have an effect in all these levels mentioned. **Figure 2** is a brief example of the possible changes that will come up with GAI for respective levels.

Moving on from the pyramid, as mentioned before, our model needs further specifications to address, since the pyramid by itself covers the responsibilities but does it in a wholistic and vague way, however, it is very comprehensive and any managerial duty we define must be fall into any of these categories. With this in mind, we wanted to expand this general definition with further responsibilities that we believe applies into every type of manager in any hierarchy or function and to do so we kept an eye on the pyramid. We believe the pyramid will create a basis for our model of responsibilities.

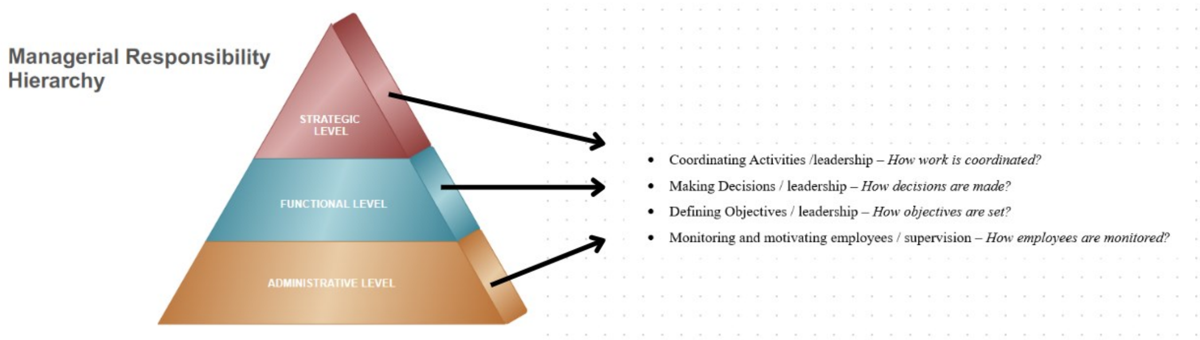
Nonetheless, we combined different approaches and ended up with the most essential 4 responsibilities. Responsibilities below and responsibilities that are introduced above are highly linked together and partially interchangeable. But it is useful to have a separation since some of the discussion will refer the pyramid while latter part will address these individual duties to analyze the impact in a more comprehensive manner. In its essence the model will be the combination of Korzynski et al. (2023) ; Sayles, (1979) ; Sayles, (1964) ; Kotter, (2017) and Birkinshaw, (2010) and their theories of managerial domain of responsibilities. Our list of responsibilities derived from these authors are listed below :

- Coordinating Activities /leadership – *How work is coordinated?*
- Making Decisions / leadership – *How decisions are made?*
- Defining Objectives / leadership – *How objectives are set?*
- Monitoring and motivating employees / supervision – *How employees are monitored?*

Therefore, the pyramid contains these universal tasks, and they are together forming the domain of research for us to investigate in understanding the change in managerial behavior. With this being said, the "managerial behaviors" are defined. Now we have four distinguished behaviors to track that are derived from the pyramid, the discussion will follow by examining the changes we observe regarding these elements.

Figure 3

Managerial Responsibility Hierarchy



Source: Author's perception

3.1 Coordinating Activities

Starting with *coordinating activities*, it's worth noting that this is primarily an *administrative-level* responsibility for managers yet any manager at any state coordinates some sort of activities therefore we define it as a universal responsibility. There are dramatic changes happening regarding this base such as organizing working time, making schedules, and bringing everyone into the same clock to create and maintain the organizational movement flow, as well as reminding and appointing tasks which all can be enhanced by the GAI. The GAI technology is capable of organizing workflows with AI backed workflow systems like Notion AI which can track and remind tasks, as well as provide deadlines eventually leading to an improvement in the information flow within the company.

At the end of the day, the focus for a manager is to search for solutions for problems that are coming from diversity, complexity, and to do things more effectively and efficiently, and therefore generate time and cost savings (Korzynski et al., 2021). Although there isn't yet enough academic research regarding organizing through GAI indeed leads to a better productivity in the firm; we observe tools like these are growing day by day with their user-friendly interfaces and usefulness they provide. Notion states that 150M+ users are entering the program every month and the numbers are ever increasing. Although using GAI's benefits are undeniable, it is important to note that organizing the activities for many organizations is still a non-procedural responsibility where people do their arrangements regarding the daily necessities, and it can't be formulized for managers to assign to AI. For instance, for a sales team having weekly meetings to see the point the team is at for achieving monthly quotas, emergency meetings for urgent situations will arise every single day. Therefore, a total handover of responsibilities of a manager to AI to coordinate the work is not happening at a full extent.

Moreover, there are important considerations that must be taken into account for managers to avoid potential hazards, such like firms with more organic organizational structure (Hellriegel et al., 1973) are seeking for autonomy of individuals to maintain the creative spirit. If a manager uses GAI to control most of the organizational coordinating activities, natural response from majority of the firms would be negative since its standardized and flexibility is damaged. Regardless, we assume if a company is quite mechanic and standardized by procedures, presumably established, it can enjoy the fruits of transferring the organization of regular activities to AI because of the reduction of necessary efforts to complete these activities can be transferred into different tasks. An example can be the factories with weekly general meetings to overlook at the production numbers can maintain the work regardless of whether it is an AI or human that makes the coordination and scheduling of meetings, taking notes, and distributing the notes to the involving parties.

One note here is that what differs from ERP systems from GAI is the key concept of learning ability of GAI, that is, if assigned, GAI will learn the preferences of users and recommend slots as it develops its understanding, at the same time, GAI will bring a big space for flexibility since ERP systems typically follow a pre-defined workflow. Lastly, GAI will generate autonomous decisions to unstructured data while other business intelligence systems will require predefined process to response to needs of the manager.

Due to its potential negative impact, these bureaucratic automations (Weber, 1947) will not be suitable for all firms. As mentioned earlier, we expect to observe adaptation of

GAI into managerial duties regarding coordinating activities where standardized rules and procedures are present for firms and when firms have an output level that is relatively consistent, however, for dynamic environments, the organic structure is a reason for creativity, therefore, for the managers it might not be the best option to go for and if so, their responsibilities might not directly be affected by the technology (Monteiro & Adler, 2022).

In essence, what we conclude here is that as Williamson (1981) discussed in his infamous paper, the transactional costs of organizing and scheduling within firms will reduce drastically when AI is assigned, therefore it will be present in the organizations and in a coordinating manager' duties in forms of :

- Coordination of employees and managers *i.e., communication, meetings, reminders.*
- Standardized and automatized documentation via integration of GAI *i.e., e-invoice*.

Another real-life example of how AI is also reducing the transactional costs within firms is an office furniture purchase from Amazon can be done via Alexa, the smart assistant of Amazon like Siri from Apple, and starting from the purchase action, many third-party activities start with the given command to obtain the furniture within days. As these systems work without flaws with each other, coordination will be handed to AI more and more due to transactional cost savings (Korzynski et al., 2023).

Therefore, with all this said, coordinative and administrative responsibilities of managers and regarding behaviors at their occupation is subject to *collaborative* change, having tendency to create a ground for total substitution in the future with its autonomous nature.

3.2 Monitoring and Motivating Employees

At all levels of the pyramid, we observe some sort of monitoring and motivation. An administrative level manager monitors their assistance staff, functional level managers monitor and motivates their team and at strategic level this duty is more important than ever. In a way, strategic level manager monitors and motivates the entire company. To extend our argument above hierarchal structure of companies, monitoring takes places in establishments as small as bakeries, a baker will be monitoring her apprentice. We believe a partial explanation to this necessity of responsibility is coming from the infamous Agent-Principal problem and monitoring is a way to reduce the possibility of lacking from the agent since an agent is equally incentivized for not working hard when monitoring is absent as well as working hard without the supervision for personal development aims.

We will now investigate this phenomenon across functions and come up to a conclusion in whether monitoring and motivating employees are indeed being affected by GAI, and if so, the level of impact of it.

Human Resources Department (HRD) is the most crucial function to begin with since we see the majority of transformation happening here. In this department, we see that responsibilities are much more interactive compared to other departments and when it comes to interaction GAI proved itself to be highly effective. ChatGPT is an extraordinary tool in here with mind – blowing conversational capabilities. Via chatbots, we expect to see motivating employees will be handled by GAI. We believe this because if the chatbots are providing human-like conversations, and we know they do, it is expected that managerial tasks that require this will be challenged with the GAI since it responds to the needs of the organization and the tasks of a manager.

For Law, Sales, Finance and Marketing Departments, as an example, we know that starting from Business Intelligence Systems and Enterprise Resource Planning Systems, tracking the organizational progress is enabled and GAI has the power to automate the tracking and has the ability to report it. To exemplify how monitoring and motivating is evolving across functions, we will provide the following assumptions between figures 4 to 11 **(see Appendix B)**.

The examples we provided above for different functions and respective managers are to justify the evolution of managerial role regarding monitoring and motivating employees as a universal duty of a manager. Our interpretation is that some of the advancements we assumed that will come up with GAI can be found in some companies in some form, especially those who heavily invested in business intelligence programs, yet the essence of our discussion is that, with GAI, such advancements will be available for all managers and therefore the transformation will be more present than ever.

On the other hand, according to our generalization the cluster of monitoring revolves around manual supervising of the tasks of other employees and motivating employees finds three forms:

- Recognition of success,
- Creating a culture that emphasizes success,

- Incentivizing success

With the examples that are provided above, we see that motivating and monitoring finds transformation with GAI. In case of adaptation, and with the efficiency increases that we discussed in the earlier chapters we believe the adaption will be necessary, such tasks of managers will be aided by GAI. Managers will begin to track performances with AI technologies and incentivize / recognize their success with online tools.

This doesn't imply a total substitution of managerial behaviors, yet we have more on table to assume there will not be any change. Therefore, we are estimating that the nature of this duty is again collaborative and somewhere in the middle between automative and non-automotive. However, we believe it tends to be replaced by GAI at a major scale because with correct prompting and adequate technological level, AI can track and motivate employees by itself. One consideration here is that, recall how employees tend to go into dishonest behaviors when they are interacting with machines instead of humans. This will be a drawback for assigning GAI as an authority, and keeping this in mind, we conclude monitoring employees and motivating them will enjoy collaboration with GAI as universal managerial duties.

3.3 Decision Making and Defining Objectives

As we have covered functional and administrative duties, the next step is to understand how managers are evolving regarding their strategical duties and such duties we will point out as making decisions and defining objectives where they are closely linked to leadership. These managerial duties find their base at strategic level but as our hypothesis suggests, these are universal duties for all managers across functions and hierarchies. A manager from administrative level or functional level also performing these duties on a daily basis regarding their own respective field.

Regardless, we will stay more on strategical level responsibilities to be able to have a comprehensive argument regarding the responsibility pyramid. Our discussion here is to have a better understanding of the proportion that a manager should be adapting into GAI by looking at the literature and recent experiments to conclude the GAI's effect at strategic level of organizations.

Recalling the pyramid of the potential application of GAI in organizations, strategic level is the top end of the hierarchy. Here we see the managers do data analysis, gather insights, and make evaluations to have an educated decision regarding which objectives to be chased. At this stage we observe massive influence from GAI, but not only from GAI, from technology itself. As we have better machines and higher computation power as well as tools to analyze, decision-makers always used these in their advantage and GAI is not a difference. Data-analysis underwent massive exposure with technological advancements and the latest change was Generative AI (Rymarczyk, 2020), therefore we can assume that decision makers can aid from generative AI to have better decisions. Moreover, *knowledge management* is also subject to have improvements from GAI. At this moment, managers who were storing the data in their files can have help from GAI since now it can spread the information by creating the correct base for it to be shared, commented, retrieved etc. As organizations make it easier to reach out to GAI, their workforce can benefit from it yet it's still open for further discussions because it brings issues like trainings, technostress, and this is an already ongoing phenomenon for big players (Argote et al., 2003 ; Gordijn & Have, 2023).

To detect the changes for a manager regarding the working life, specifically regarding strategical duties that includes decision making and setting objectives we need to understand to which degree AI is performing better than managers, therefore we can conclude whether it has a subsidiary effect, and the actors of strategical decision making has been replaced with GAI. Therefore, we need to look at the comparisons in the literature however, what we observe is that GAI has not yet completed its overtaking transformation and at this point it is more of a tool for managers to enhance their output since it has astonishing capabilities but still lack some essential skills to be assigned as an authority.

IBM's Project Debater validated AI's improvement and usefulness however concluded with how humans are still the leading species regarding balancing different point of views (Slonim, 2018). The search for goals and objectives can't be concluded with GAI's appearance in businesses, it's still a managerial responsibility that GAI can only be helpful as an addition since it has its own struggles. Tegmark, (2017) notes on this:

> *If I had to summarize in a single word what the thorniest AI controversies are about, it would be goals.* (p. 249)

Moreover, Tegmark, (2017) discusses that GAI performs best when it is:

Directed towards tackling a singular goal. Indeed, the success of machine learning techniques, such as reinforcement learning, is based on algorithms that reward choices that get closer to a pre-specified goal (p. 249)

Another point is that the managers also consider solutions that we know by out-of-the-box-thinking. It is a key component for many firms to be creative and differentiated. More procedural decision-making that comes from GAI, leads firms to be more similar to each other as mentioned before, for example for finance industry they use similar finance bots to receive investment ideas, but they should be cautious with the fact that the main engine for a computer is its sophisticated algorithms and prior interference with the datasets and both cases indicate to an impossibility for an out-of-the-box-thinking which will lead to a reduction in differentiation. In fact, surprisingly, Financial Times (Johnson, 2017) reported that humans made better investments rather than AI. This is especially true given the fact that managers who can go against the market's wisdom at their own high-risk, knowing that they can be wrong as well, makes them unique in comparison to GAI where AI can never know it is wrong, but humans will always be considerate, and they will avoid having committed into wrong decisions by noticing the absurdity.

Further discussions come from Raisch & Krakowski (2021) and their *paradox theory.* The context is the clarification of the nature of duties by naming them "the augmentation and automation" as we referred previously the automative nature of the work in our discussion. We have discussed that; highly cognitive tasks, physical tasks, and other classifications are harder to replace via GAI, and proved it with exposures and monetary returns at various industries and professions. In their terms, automation is the degree that a machine can replace a human and augmentation refers to human and machine collaboration for a mutual goal.

As it aligns with our discussion, the degree of application will be determined by the organization's tendency towards augmentation or automation. They argue that for managers the distinguishment simply cannot be done easily. For some tasks which has an automative spirit like filling invoices or other tasks, organizations will have a natural tendency to have a replacement of workforce with the GAI, however, the nature of many managerial problems are complex by nature. There can be a rule-based automation where machine can follow a given set of tasks and can even lead customers accordingly, yet organizations can also prefer managers to use an exploratory way towards the problems and analyze them further. The paradox is as follows: The augmentation of managerial tasks will result in successive automation, which in turn will create further augmentation. It is especially important for uneasy and rare tasks to discover the problem where for many managerial problems a singular formula cannot fit for all (Davis & Marcus, 2015; Korzynski et al., 2023).

Some final words for this discussion follow Agrawal (2018), who stated that although AI brings tremendous enhancements, it is still more of an intelligent co-worker that does particularly good predictions. However, businesses and managerial duties require further complex decisions, and therefore managerial duties don't entirely change but there is a substantial amount of change present and the amount will increase in time, since at the moment, role changes are to make this co-working more efficient. Regardless, judgements and final actions will be preserved within managers for a longer while. In the near future, this complementary direction that GAI's adapting will be even bigger, there will be different tasks and different algorithms where managers and AI works closely together. They will use the help of GAI to gather data, having it analyzed, catching up for market trends, and use the information to produce managerial output to keep the organization differentiated and utilized as efficient as possible. Managers will accomplish this with their own unique attributes regarding complex-decision making. Regardless, the possibilities of AI in managerial decision-making are becoming not only bigger, but also encompassing a wider scope of activities and business functions in organizations.

With all this said, the conclusion is that, just like other responsibilities of managers, also at the strategic level we see benefit of co-working with managers and GAI, we also believe that it doesn't have a tendency to be replaced by the technology at a full extent because of the limitations of GAI and powerful decision-making capabilities of humans.

3.4 Interactive Duties

Based on our discussion above, some of the managerial duties have an automative nature and some of them have a more interactive structure. We believe that interactive nature of the work might also be an important consideration when grouping managerial roles based on their nature.

Some managers such as Sales, Human Resources, administrative level managers and managers whose functional level duties are highly interactive, as well as managers who's derived responsibilities from the pyramid requires human interaction at a higher degree will be classified as high-level interaction managerial duties. This argument will follow the same logic for managers who doesn’t involve in human interaction and classify them as low-level interaction duties. Examples can be Information Technologies Managers, managers whose work at their functional level does not necessarily require human interaction, and managers who can perform their decision making without interacting with people, or to a relatively low extent.

Following table demonstrates our classification and forms the basis to discuss our finding and form the hypotheses.

TABLE 6

Nature of Managerial Roles Prediction

Categorization of Managerial Roles

Department	Interaction with others	Automative Nature of Work
Team Leaders at IT	Low Interaction	High
Human Resources	High Interaction	Moderate
Marketing	Moderate Interaction	Moderate
CEO	Moderate Interaction	Low
Sales	High Interaction	Low
Production	Low Interaction	High
Law	Moderate Interaction	Moderate

Note. We build this on Figure 1 to enlarge the managerial nature of work perception of ours. Source: Author’s Perception

3.5 Summary of the Discussion and Hypotheses

At the beginning of this paper there was nothing but a single question to be deeply evaluated. How is this groundbreaking revolution of GAI affecting the managerial class of the businesses around the world? We started to investigate from the technical aspects of GAI to see its capabilities, then we questioned its applications in the labor market where we observed some jobs are affected from it more than the others. Then, we concluded that we could define a concept such as the nature of the work. It enlightened us about the complexity and strategic decision making that job's require is strictly related with the replacement rates.

We took a step further to understand how GAI influenced the managers. The labor market is affected, and it signals that the workers must be get affected too. We believed that this is the hidden pattern that we needed to investigate. To have a clear understanding of this problem, we supplied the thesis with multiple definitions and theories of managerial duties, and we examined to see if we could catch a connection with whether the capabilities of GAI are interacting specifically with some of the responsibilities, and indeed we caught connections.

We realized that some of the duties, such like strategic decision making, can be enhanced with GAI. On the other hand, Administrative and Functional responsibilities, we see partial replacements of human labor with machines, therefore once more we estimated that regarding these two level a manager can use GAI as an enhancement tool for their work. Yet still, for some responsibilities it is not yet feasible to rely on this technology yet because of partial superiority of human mind and incapabilities of the GAI.

With this summary, we created following hypotheses to investigate at the analysis section. Before presenting the hypothesis, recall that, one assumption we made is that we categorized jobs under two categories. These are the interaction with other people and automative tasks level it contains based on our perceptions. Based upon this categorization, we could compare different functions.

The concluding note is these hypotheses were born from the nature of the work and its relationship with GAI discussion to understand the change in managerial behavior, which can be taken as the research question.

H_{1a} – Managers of male gender performs better with GAI than managers of gender female.

H_{1b} – Managers of large firms performs better with GAI.

H_{1c} – Managers of postgraduate degree performs better with GAI than managers of graduate level degree.

H_{2a} – As automative level of work increases, managers will increase their performance with GAI.

H_{2b}- As automative level of work increases, managers will be more willing to adapt to GAI.

H_{3a} – As interaction level of work increases managers will utilize GAI more to experience performance improvements.

H_{3b} – As interaction level of work increases managers will be more willing to adapt to GAI.

H_{4a} – As interaction level of work increases managers will expose to less technostress.

In the following section, we will start testing these questions and present our methodology and findings.

Chapter 4
Methodology

4.1 Sample and Survey Design

To get information to evaluate the change in behavior, the natural choice was to make direct connections with the owners of the occupation and ask them to evaluate the strong assumptions of the literature to see whether they are indeed experiencing what we are foreseeing as academics. We formed a questionnaire and created a survey in which the aim was to quantify the problem. Turning individual experiences into measurable results we included mainly quantitative questions. The philosophy of our research is pragmatism**,** since we aim to understand causal relationships (i.e., the cause is GAI and the result is change in behavior) and quantify a phenomenon, however, parallelly we are interpreting subjective experiences (i.e., participants' personal acquaintances).

Although the research question is partially formed, we will still move on with inductive reasoning since we aim to develop generalizations out of these observations and understand patterns from these observations. The survey data is used to test our hypotheses. To avoid complexity, we didn't involve uncommon methodology, instead, a major part of the survey is formed by questions that fit to a Likert Scale and the remaining part was formed mainly by dichotomous questions.

The data is collected via an online survey in which we sent out to 240 managers, executives or people who oversee a sort of decision-making between the period of November 2023 to January 2024. We reached out to these people via our networks and asked them to send it to their networks. Furthermore, we aimed to group managers across business functions. These functions include sales, marketing, human resources, law, production, firm owners, IT managers, etc. At the end of survey, we got fifty responses from these managers. One thing we consider was to send out the survey to variety of managerial cast to have a collective understanding of the change in managerial behavior. Our aim is to assess whether the predefined managerial responsibilities are indeed being challenged by the development and integration of the GAI, their current relationship with it, their expectations of its exposure in the future and the immediate emotional considerations regarding GAI's presence. We also collected demographical data and company data regarding size to enable ourselves for further analysis.

The data collection process strictly adhered to ethical guidelines. Informed consent was obtained from all participants, ensuring they were fully informed about the research aims, their voluntary participation, and the confidentiality of their information. The collected data remains completely anonymous, with all identifiable information removed or disguised to ensure participant privacy. Furthermore, the data gathered will be used solely for the purposes of this research project and will not be shared or used for any other study or purpose.

For the dichotomous questions, we strictly questioned whether there is an exposure of GAI at managerial responsibilities. We followed three parent dimensions of managerial role to see whether the effect takes place in any of these areas. The answers could be given in Yes – No form. This part of the survey enabled us to have an overview of the impact while more in-depth questions were more useful for seeing the detailed impact.

In total, we obtained 50 responses, which translates to a response rate of 19.46%. The titles of the managers did show variety (i.e., sales executive, sales manager, business development manager), but we grouped them into major functions such as Marketing, Law, etc. One assumption we made here is that, received responses from different job titles is justified since as investigated earlier, regardless of the size, title, domain or place, the duties of managers show high level of likelihood and differentiate from each other within the functional level (where they perform their occupation). Following this logic, all the respondents are considered eligible to be participants.

4.2 Statistical Description

The data we collected has identifiers of firm size, degree of education, gender, managerial role, and Types of GAI preference. As mentioned earlier, job positions are gathered under major functions. **Table 7** shows the distribution of identifiers.

Based on **Table 7** we see an expected distribution amongst managerial occupations, with marketing and vice managers share the highest proportions (20% respectively). It can be said that participants are mostly male (70%) , they are mainly Bachelor's and Master's graduates (total of 94%) . A little more than half of the respondents are from firms with 200+ employees, indicating a corporate structure, while smaller and medium size companies share the rest while small size companies have %10 more representation. As expected, 41 respondents out of 50 stated they are utilizing ChatGPT in one way or another, aligning that it being the most popular GAI tool in the world. We also see a visualization tool (Mid Journey) received 12% of usage, it might indicate that managers started to prepare their visuals via GAI. The location of respondents is from Istanbul and Ankara.

For convenience, we recoded the questions as V1, V2… V20. The corresponding relationship is shown at **Table 9** with the descriptive statistics. In addition, to do accurate comparisons, we thought that using PhD candidates may not create powerful estimates since their responsive pool is extremely small. Therefore, we combined the educational difference between graduate and postgraduate by combining master's and PhD degree holders together. Lastly, for simplicity, the representation of the answers turned into numeric data in the following way : "Strongly Disagree" = 1, "Disagree" = 2, "Neutral" = 3, "Agree" = 4, "Strongly Agree" = 5.

Lastly, Managerial roles are coded as: "CEO" = 1, "Human Resources Manager" = 2, "Law Manager" = 3, "Marketing Manager" = 4, "Production Manager" = 5, "Sales Manager" = 6, "IT Team Manager" = 7.

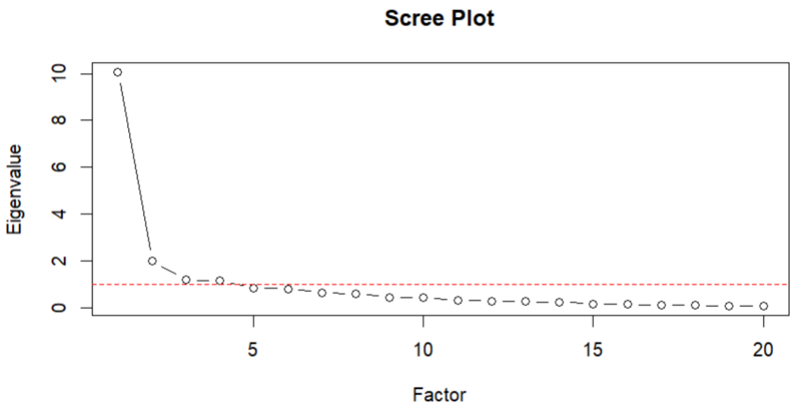
4.4 Factor Analysis

We conducted Exploratory Factor Analysis (EFA) to help reduce the dimension of questions that target the same constructs and reveal those constructs and Confirmatory Factor Analysis (CFA) to validate our findings. To improve reliability, we followed Bartlett Test of Sphericity (BTS) and Kasier-Meyer-Olkin (KMO) Measure. Tests report strength in our dataset, for BTS, chi-square statistic is 1655.413 with $p < .01$, indicating there is a significant difference from the identity matrix. KMO reported sampling adequacy of 0.87 with constantly exceeding 0.8 at all values. Both results created the base for us to conduct EFA analysis.

We used the correlation matrix for the questions (V1 to V20) to conduct the analysis. Based on the matrix, we performed Kaiser's criterion and scree plot to reveal the constructs. Criterion reported four important values with the following eigenvalues: 10.07 2.02 1.18 1.15.

Figure 12

Scree Plot of EFA



Source: R

Moreover, to simplify and interpret the factor structure, we adapted factor matrix rotation. Factor loadings of the findings (rotated component matrix) are shown at table **x.** We find that first construct explains 26% of the variance while for the second it is 15%, for the third, 9% and the fourth one explains 16% of the total variance with a cumulative score of 65% is reached. Communalities range from 0.38 to 0.84. Rotated loadings are shown in following table.

Table 8

Factor Loadings extracted from EFA

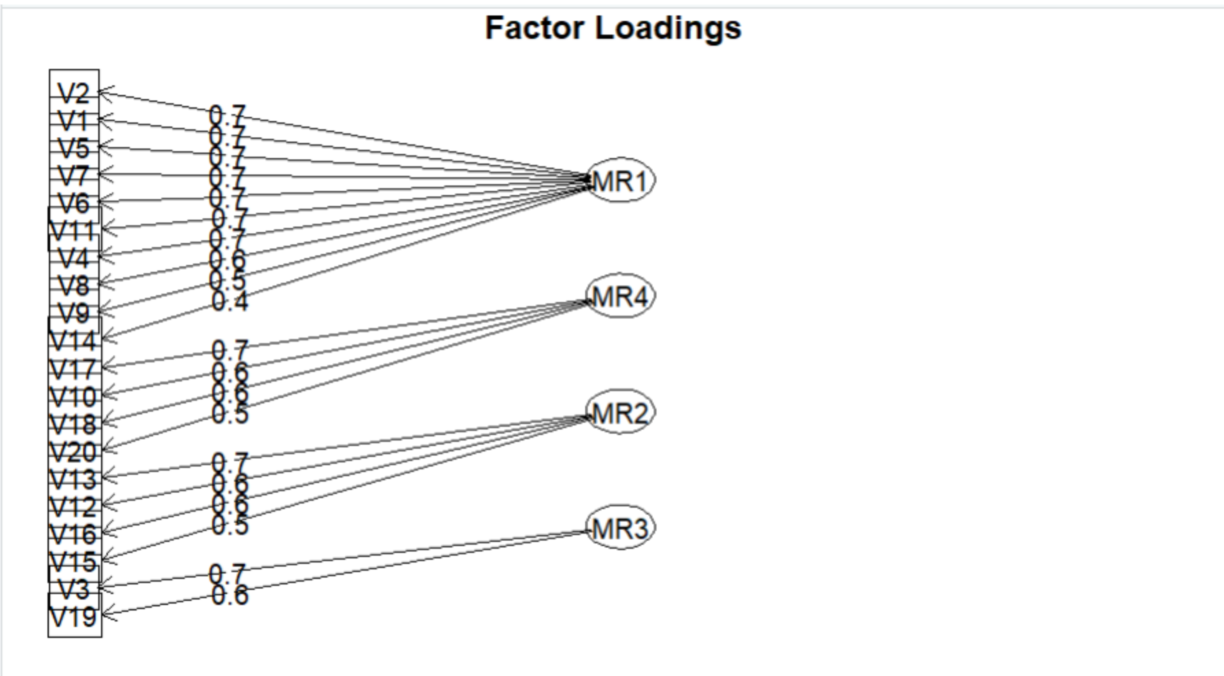
Variables	Constructs			
	MR1	MR2	MR3	MR4
V1	0.7056028629			
V2	0.7208060515			
V4	0.6514154313			
V5	0.7054025019			
V6	0.6911476278			
V7	0.6912477001			
V8	0.5826405150			
V9	0.5436756482			

V11	0.6647374186			
V14	0.4034957243			
V12		0.6300546980		
V13		0.7396783615		
V15		0.5382122732		
V16		0.5950870131		
V3			0.6557622448	
V19			0.6155560068	
V10				0.5947834155
V17				0.7043413673
V18				0.5809264928
V20				0.5204974261

Based on these factor loadings, we performed the following diagram to demonstrate construct and survey questions relationship.

Figure 13

Construct Structure Based on Factor Loadings



Source: R

Based on this data, we concluded that there are 4 reflective constructs, each created by different survey items. By looking at the questions **(see table 9)**, we concluded that *MR1* in dicates better capabilities at performing the occupation, *MR2* indicates technostress, and *MR4* indicates adaptiveness of managers into GAI. *MR3* was difficult to conceptualize. To assess th e reliability of internal constructs, we conducted Cronbach's alpha to. Test reported a Cronbac h's alpha coefficient of 0.74 (95% CI [0.49, 0.89]). The standard alpha coefficient was also 0. 74.

Table 9

Descriptive Statistics and Renaming

Questions	Variable Rename	Mean	SD	N
Generative AI has positively impacted the quality of my work.	V1	3.2	0.9	50
Generative AI has improved the efficiency in my department.	V2	4.1	0.8	50
I believe Generative AI is a valuable addition to the workforce in my company.	V3	2.9	1.0	50
Generative AI has reduced the costs for some of our operations.	V4	3.5	0.7	50
I use GAI to create segments for the data I'm using.	V5	4.0	0.6	50
Generative AI improved the efficiency of coordinating activities and completing basic tasks in my managerial role.	V6	3.8	0.5	50
Generative AI improved my ability to track employees and monitor their performance effectively.	V7	4.2	0.8	50
Generative AI positively impacted my ability to set goals and make complex decisions regarding the work.	V8	3.9	0.7	50

Generative AI improved my ability to generate creative ideas.	V9	3.6	0.7	50
Generative AI improved my overall performance regarding managerial tasks.	V10	4.5	0.5	50
I have observed an increase in employee engagement and interaction due to the use of Generative AI in my managerial tasks.	V11	3.7	0.9	50
I believe that Generative AI could potentially replace some aspects of my managerial role.	V12	3.1	0.6	50
The possibility of my replacement with GAI stresses me.	V13	3.4	0.7	50
I have access to the necessary resources and support for using Generative AI in my role.	V14	3.9	0.8	50
I have received training on how to use General AI tools effectively.	V15	4.2	0.9	50
The trainings about GAI stressed me.	V16	2.8	1.1	50
I am actively seeking opportunities to further integrate Generative AI into my managerial activities.	V17	3.3	0.8	50
I will start training if GAI becomes a necessity in my occupation.	V18	4.2	0.7	50
I am confident in my ability to adapt to changes driven by Generative AI in my managerial role.	V19	3.8	0.6	50
I feel like if I fail being good at GAI, I can't be competent for my job in the future.	V20	3.6	0.5	50

4.3 Mean Value of Constructs

Based on the constructs created by EFA and the answers we collected, before we conduct statistical analysis, we wanted to report the mean values for each construct within the

Likert Scale. To do so, we followed basic calculations by adding the means values of questions for each construct and divided the total to the variable number that construct contains.

Improvement at Managerial Tasks, the overall scoring was calculated by averaging the scores across the relevant questions. The average score for it was found to be 2,70 .

This suggests that, on average, respondents tended to report between Neutral to Disagree. The individual item scores contributing to Performance Increase with GAI ranged from 2,9 to 4.15 , indicating variability in question item means.

Similarly, the scoring for Technostress , was computed by averaging the scores of the associated Likert scale questions. The overall score for Technostress was 3,38 while individual contributing scores ranging from 2,8 to 4,2. Willingness to Adapt to GAI, averaged mean of 3,9 with individual question means ranging from 3,3 to 4,5,

4.4 Comparative T-Tests, Linear Regressions and MANOVA tests

4.4.1 Analysis of Gender and Constructs

For the control variables, we conducted comparative t-tests between the values to compare mean values between groups. For gender, we compared male and female for constructs. Then, to strengthen our findings, we backed the findings with linear regressions when applicable. **Table 10** and **11** demonstrates the findings for gender analysis.

Table 10

Results of Welch's T-tests Examining Gender to the Target Construct

Constructs	Males		Females		t (25)	*p*	Cohen's d
	M	SD	M	SD			
Performance Increase with GAI	0.12	0.97	-0.27	1.06	1.23	.23	0.395
Technostress by GAI	-0.162	1.00	0.04	1.04	-0.174	.86	-0.05
HC*	-0.167	0.92	0.39	1.09	-1.72	.10	-0.568
Willingness to Adapt to GAI	-0.118	0.967	0.275	1.056	-1.23	.23	-0.395

Note. Mean parameter values for each of the analysis are shown for the males (*n* = 35) and females (*n = 15),* as well as the results of *t* tests (assuming unequal variance).

Note.* HC stands for the construct 3 which we referred as hard to conceptualize earlier in the paper due to its small amount of survey question coverage (2).

Table 11

Results of Linear Regression Examining Gender to Target Construct

Constructs	Intercept	Estimate	SE (Male)	95% CI LL	95% CI UL	*p*
Performance Increase with GAI	-0.275	0.3922	0.306	-2.556	2.391	0.207
Technostress by GAI	0.038	-0.055	0.312	-2.39	2.00	0.861
HC	0.388	-0.555	0.301	-2.222	2.645	0.072
Willingness to Adapt to GAI	0.274	-0.392	0.307	-3.278	2.489	0.207

Note. Controlled by females. Number of participants = 50, df = 48. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

The analysis of performance increase construct scores revealed no statistically significant relationship with gender. Both a t-test (t(25) = 1.23, *p = .23*) and linear regression (t(48) = 1.28, *p = .20*) failed to find significant associations. The linear regression model, with an F-statistic of 1.636, indicated that gender did not significantly predict performance increase construct scores (β = 0.392, SE = 0.307, *p = 0.207*). Moreover, adjusted R-squared value of 1.28%, collectively suggest that gender, whether male or female, does not play a statistically significant role in determining performance increase with GAI.

The analysis of Technostress by GAI revealed no statistically significant relationship with gender. Both a t-test (t(26) = -0.1736, *p = .86*) and linear regression (t(48) = -0.176, *p = .86*) failed to find significant associations. The linear regression model, with an F-statistic of 0.03, indicated that gender did not significantly predict Technostress by GAI scores (β = -0.05, SE = 0.312, *p = 0.861*). Moreover, the adjusted R-squared value of 0.001 suggested that gender, whether male or female, did not explain a substantial portion of the variance in Technostress by GAI scores. Therefore, we conclude that the variable gender (male, female) does not have a statistically significant relationship with Technostress by GAI.

For MR3, both a t-test (t(23) = -1.72, *p = .10*) and linear regression (t(48) = -1.841, *p = 0.07*) suggest a statistically significant relationship at a 90% confidence interval (CI). The linear regression model, with an F-statistic of 3.39, indicated that gender does have a statistically significant relationship with MR3 scores (β = -0.555, SE = 0.301, *p = .072*). Moreover, the adjusted R-squared value of 4.65% suggests that gender explains a small portion of the variance in MR3 scores. Therefore, we conclude that the variable gender (male, female) does have a statistically significant relationship with MR3 at a 90% CI.

For Willingness to Adapt to GAI, both a t-test (t(25) = -1.23, *p = .23*) and linear regression (t(48) = -1.28, *p = .20*) indicated no statistically significant relationship. The linear regression model, with an F-statistic of 1.63, further confirmed that gender does not have a statistically significant relationship with Willingness to Adapt to GAI scores (β = -0.3921, SE = 0.307, *p = .207*). Additionally, the adjusted R-squared value of 1.28% indicated that gender explains only a small portion of the variance in Willingness to Adapt to GAI scores. Thus, we conclude that the variable gender (male, female) does not have a statistically significant relationship with Willingness to Adapt to GAI.

4.4.2 Analysis of Degree of Education and Constructs

Originally, our dataset represented four levels of education from high school to PhD. Considering low sample sizes of high school and PhD, we combined them into graduate and post graduate groups to examine whether there is a difference in managerial behavior change based on our constructs.

Table 12

Results of Welch's T-tests Examining Degree of Education to the Target Construct

Constructs	Graduate		Post-Graduate		t (42*)	*p*	Cohen's d
	M	SD	M	SD			
Performance Increase with GAI	-0.059	0.999	0.089	1.036	-0.499	0.620	-0.145
Technostress by GAI	0.865	0.922	0.153	1.114	0.848	0.402	-0.254
HC	0.091	1.040	0.137	0.945	0.801	0.427	0.227

Willingness to Adapt to GAI	0.077	1.096	0.115	0.849	0.693	0.491	-1.104

Note. Mean parameter values for each of the analysis are shown for the postgraduates (*n* = 19) and graduates (*n = 31),* as well as the results of *t* tests (assuming unequal variance).

Note.* Df changes for each construct because of the complicated df calculation method of Welch's T- test. Degrees of freedom ranges from 35.473 to 46.818, therefore we assigned 42 as a round average.

Table 13

Results of Linear Regression Examining Degree of Education to Target Construct

Constructs	Intercept	Estimate	SE (postgrad)	95% CI		*p*
				LL	UL	
Performance Increase with GAI	0.059	0.146	0.290	2.918	2.568	0.617
Technostress by GAI	-0.102	0.255	0.289	2.304	2.0189	0.383
HC	0.091	0.228	0.290	2.179	3.124	0.427
Willingness to Adapt to GAI	0.077	-0.191	0.290	3.080	2.294	0.513

Note. Controlled by graduates (Bachelor's). Number of participants = 50, df = 48. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

For Degree of Education, we compared graduate and undergraduates for constructs with T-tests and linear regressions. Between graduates and postgraduates, the mean scores for the Performance Increase with GAI were M = -0.06 and 0.09, respectively ($t(39.58) = -0.50$, $p = .6207$, 95% CI [-0.74, 0.45]). However, the linear regression analysis did not yield significant results, as evidenced by the F-statistic of ($F(1, 48) = 0.2535$, $p = .617$). The degree of education did not statistically predict scores on the Performance Increase with GAI (β = 0.146, SE = 0.291, $t(48) = 0.503$, $p = .617$, 95% CI [-0.446, 0.739]). Additionally, the adjusted R-squared value suggested that the model explained only 0.53% of the variance in Performance Increase with GAI scores. Therefore, we did not find a statistically significant relationship between the degree of education and Performance Increase with GAI scores.

For Technostress by GAI, a Welch Two Sample t-test comparing the mean scores between graduates and postgraduates yielded a non-significant result (t = -0.84744, df = 35.473, $p = 0.4024$). Similarly, in the linear regression analysis, the degree of education did not significantly predict scores on the Technostress by GAI construct (F(1, 48) = 0.7752, $p = 0.383$). The coefficient for the degree of education variable was not statistically significant (β = 0.2547, SE = 0.2893, t(48) = 0.880, $p = 0.383$). Moreover, the adjusted R-squared value indicated that the model explained only a negligible amount of the variance in Technostress by GAI scores (Adjusted R-squared = -0.00461). Thus, there was no statistically significant relationship observed between the degree of education and Technostress by GAI scores.

For Construct 3, a Welch Two Sample t-test comparing the mean scores between graduates and postgraduates yielded a non-significant result (t = -0.80126, df = 43.493, $p = 0.4273$). Similarly, in the linear regression analysis, the degree of education did not significantly predict scores on the construct (F(1, 48) = 0.6175, $p = 0.4358$). The coefficient for the degree of education variable was not statistically significant (β = 0.22773, SE = 0.28981, t(48) = 0.786, $p = 0.436$). Moreover, the adjusted R-squared value indicated that the model explained only a negligible amount of the variance in scores (Adjusted R-squared = -0.008). Thus, there was no statistically significant relationship observed between the degree of education and scores.

For Willingness to Adapt to GAI construct, the Welch Two Sample t-test comparing the mean scores between graduates and postgraduates showed no statistically significant difference (t = 0.69317, df = 46.818, $p = 0.4916$). Similarly, in the linear regression analysis, the degree of education did not significantly predict scores on the Willingness to Adapt to GAI construct (F(1, 48) = 0.4338, $p = 0.5133$). The coefficient for the degree of education variable was not statistically significant (β = -0.1912, SE = 0.2904, t(48) = -0.659, $p = 0.513$). Moreover, the adjusted R-squared value indicated that the model explained only a small portion of the variance in Willingness to Adapt to GAI scores (Adjusted R-squared = -0.01). Therefore, there was no statistically significant relationship observed between the degree of education and Willingness to Adapt to GAI scores.

4.4.3 Analysis of Firm Size and Constructs

For the firm sizes, we combined small (1 - 50) and mid-sized (51 - 200) firms as small firms compared to large firms (201 +) to bring sample sizes closer to each other. Originally mid-sized firms accounted for 9 respondents (18% of dataset). We conducted Welch Two

Sample t-test comparing the mean scores between small and large firms for each construct. **Table 14** demonstrates the findings of the t-test.

Table 14

Results of Welch's T-tests Examining Firm Size to the Target Construct

Constructs	Large Firms		Small Firms		t	*p*	Cohen's
	M	SD	M	SD	(44*)		d
Performance Increase with GAI	-0.159	0.992	0.186	0.999	1.221	0.228	0.995
Technostress by GAI	0.197	0.812	0.231	1.159	1.489	0.144	0.435
HC	-0.109	1.037	0.128	0.961	0.835	0.408	-0.235
Willingness to Adapt to GAI	-0.211	0.831	0.248	1.136	1.607	0.116	-0.467

Note. Mean parameter values for each of the analysis are shown for the small firms (n = 23) and large firms (n = *27),* as well as the results of t tests (assuming unequal variance).

Between small and large firms, the mean scores for the Performance Increase with GAI were M = -0.159 and 0.186 respectively, (t(46.64) = -1.22, p = .23), for technostress construct, the test reported (t(38.54) = 1.49, p = .144). Construct 3 reported (t(47.63) = -0.83, p = .408) and Willingness to Adapt to GAI reported (t(39.65) = -1.607, p = .116)**.** Hence, firm size concluded not having any statistical significance, but between small and big firms for Willingness to Adapt to GAI, the existence of a peak mean difference is observed.

4.4.4 Analysis of Different Managerial Occupations and Constructs

We started with conducting box plots for roles and constructs **(see figure 14-17**), after we followed with ANOVA and regressions. **Table 15 and 16** demonstrates the findings of the conducted tests. ANOVA test reported for Performance Increase with GAI (F(6,43) = 0.763, $p = .603$), where $\eta^2 = .096$, indicating statistical insignificance for mean differences across different managerial occupations for target construct. Regression supported this model with an F statistic of 0.76 at 43 df, $p = .60$) indicating that no individual significance across managerial roles (Adjusted R-squared = -0.03).

Table 15

Results of Linear Regressions Examining Different Managerial Occupations to Target Constructs

Constructs	Estimate	SE	95% CI LL	95% CI UL	*p*
Performance Increase with GAI					
Intercept	0.010	0.320	-2.840	2.118	0.976
Human Resources Manager	-0.222	0.466	-2.840	2.118	0.636
Law Manager	-0.926	0.786	-2.840	2.118	0.245
Marketing Manager	0.381	0.466	-2.840	2.118	0.418
Production Manager	-0.237	0.556	-2.840	2.118	0.672
Sales Manager	-0.098	0.454	-2.840	2.118	0.830
Team Leader	0.418	0.556	-2.840	2.118	0.456
Technostress by GAI					
Intercept	0.166	0.335	-2.502	1.938	0.624
Human Resources Manager	-0.378	0.487	-2.502	1.938	0.442
Law Manager	-0.150	0.820	-2.502	1.938	0.855
Marketing Manager	-0.070	0.487	-2.502	1.938	0.887
Production Manager	-0.213	0.580	-2.502	1.938	0.716
Sales Manager	-0.187	0.473	-2.502	1.938	0.696
Team Leader	-0.205	0.580	-2.502	1.938	0.726
Construct 3 - HC					
Intercept	0.035	0.297	-1.868	2.178	0.908
Human Resources Manager	0.533	0.432	-1.868	2.178	0.224
Law Manager	-0.086	0.728	-1.868	2.178	0.907
Marketing Manager	-0.323	0.432	-1.868	2.178	0.459
Production Manager	-0.395	0.515	-1.868	2.178	0.448
Sales Manager	0.821	0.421	-1.868	2.178	0.058
Team Leader	-0.019	0.516	-1.868	2.178	0.971
Willingness to Adapt to GAI					
Intercept	0.039	0.334	-3.224	2.451	0.909
Human Resources Manager	-0.114	0.486	-3.224	2.451	0.816
Law Manager	-0.346	0.819	-3.224	2.451	0.675
Marketing Manager	-0.119	0.486	-3.224	2.451	0.807

Production Manager	-0.011	0.579	-3.224	2.451	0.985
Sales Manager	0.182	0.474	-3.224	2.451	0.703
Team Leader	-0.181	0.579	-3.224	2.451	0.756

Note. Controlled by randomly chosen job category (CEO's). Number of participants = 50, df = 43. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 16

Means, Standard Deviations, and Multiple-Way Analyses of Different Job Categories in Target Constructs

Construct	F(6,34)	*p*	η^2
Performance Increase with GAI	0.763	0.603	0.096
Technostress by GAI	0.117	0.994	0.016
HC	2.067	0.077	0.224
Willingness to Adapt to GAI	0.135	0.991	0.018

ANOVA test reported for Technostress by GAI (F(6,43) = 0.017, $p = 0.994$)), wher e η^2 = . 0.016 , indicating statistical insignificance for mean differences across different mana gerial occupations for target construct. Regression supported this model with (F(6,43) = 0.12, $p = .99$) with no individual significance across managerial roles (Adjusted R-squared = -0.12) .

For HC construct, we obtained (F(6,43) = 2.067, p = 0.0771), where η^2 = . 0.224 , indicating statistical insignificance at 90% CI level for mean differences across different managerial occ upations for target construct. Regression supported this model with (F(6,43) = 2.067, $p = .08$) with no individual significance across managerial roles.

Willingness to Adapt to GAI construct reported (F(6,43) = 0.135, p = 0.991) where η^2 = .018, indicating statistical insignificance for mean differences across different manageria l occupations for target construct. Regression supported this model with (F(6,43) = 0.134, $p = .99$) with no individual significance across managerial roles.

4.4.5 ANOVA for Interaction and Automation Groupings for Different Managerial Occupations at Target Constructs

We had grouped different managerial groups under their respective nature of tasks (**see Table 6)**. Across interaction and automation groups ANOVA test findings are demonstrated in **Table 17.**

Table 17

Analysis of Interaction and Automation Level Groupings Across Managers at Target Construct

Groupings	F(2,47)	p	η^2
Interaction Group			
Performance Increase with GAI	0.322	0.726	0.013
Technostress by GAI	0.274	0.762	0.015
HC	0.708	0.498	0.029
Willingness to Adapt to GAI	0.096	0.909	0.004
Automation Group			
Performance Increase with GAI	0.064	0.938	0.002
Technostress by GAI	0.084	0.92	0.003
HC	3.811	0.029*	0.134
Willingness to Adapt to GAI	0.277	0.759	0.012

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

F(2,47) representing the three interaction and automation groups we conducted while 47 responds to the amount of response we analyzed. For construct three p value was at statistical significance under 95% CI yet for the same reasons we are not analyzing it further. Consistent p values across different categories indicated that there is not a statistically significant relationship between interaction and automation levels for managers of various occupations at target constructs.

Chapter 5
Discussions

Our tests aimed to find a relationship between gender, degree of education, firm size, different managerial roles, and different levels of job natures for the constructs we extracted from EFA analysis. Each heading discusses the findings under its own category. The results were quite unexpected since we failed to get statistically significant results that supports our hypotheses. Although there are minor findings at construct three, we will not analyze or discuss them further since the creation of construct disabled us to properly connect it with a concept. One concern here we had was that it had only two questions forming it and we saw no similarity between these elements of the construct. With this being said, we will stress our findings at other constructs. **Table 18** reports the conclusions for our hypotheses. We didn't conduct further analysis to understand the directions after our generic analyses reported statistical insignificance between groups at target constructs.

Table 18

Table of hypothesis testing results

Hypothesis		Conclusion	Remark
Hypothesis 1a	Male managers - Performance increase	√	n
Hypothesis 1b	Large firms - Performance increase	X	n
Hypothesis 1c	Postgraduates - Performance increase	√	n
Hypothesis 2a	Automation – Performance increase	du	n
Hypothesis 2a	Automation – Willingness for Adaptation	du	n
Hypothesis 3a	Interaction – Performance increase	du	n
Hypothesis 3b	Interaction – Willingness to Adapt	du	n
Hypothesis 3c	Interaction - Technostress	du	n

Note: reject *(x),*accept (√) , direction unknown (du), non-significant correlation (n).

5.1 Demographics

5.1.1 Analysis for Gender

None of the managerial roles had a statistically significant mean difference regarding the constructs for t-tests and regressions. This creates clear evidence to argue that gender being an insignificant element for managerial behavior change and it is not surprising. We observe that gender equality at managerial positions is at its peak and ever increasing. Diversity, equality, and inclusion are trending points to address for firms of various size. As women are increasingly welcomed to managerial positions, we can argue that this could be one of elements which together creates the base to develop managerial competence independent of the gender. Using technological tools is one aspect of managerial competence and for the same positions in companies' gender didn't report significance for our constructs.

5.1.2 Analysis for Firm Size

We started with combining different firm sizes into entities with similar sizes and conducted our analysis based on two firm sizes: Large firms and small firms. We found no clear evidence that firm size effects Performance Increase with GAI, Technostress by GAI or Willingness to Adapt to GAI. The results were surprising because our initial estimation was to observe a clear difference between firm sizes across our constructs. From the literature we know that small firms have a tendency to acquire technology since they want to differentiate themselves to survive, they are easier to adapt to changes because of their organic structure and instead of optimizing their work, they are more inclined to create value propositions to find a safer spot in the market.

However, statistical insignificance made us consider the effects of utilizing GAI. We suspect that managers may not yet fully adapted to GAI to experience our constructs, hence responded similarly to our questions. We remember that the factors for adaptation into a new technology consist of many elements and at this point of time managers in Turkey may not yet are utilizing GAI. We also consider that the leverage that big firms have regarding R&D budgets, employee trainings and access to bigger resources may played a role that now both small and big firms are going through similar processes but due to different reasons. It is a possibility that while small firms are looking for ways distinguish themselves in the market and adapting to GAI, big firms are providing procedures of adapting to it and managers across firm sizes are getting exposed to it at a similar level. We also suggest recalling that our sample size was very concentrated and small to take out generalizations.

5.1.3 Analysis for Degree of Education

Higher degrees of education did not prove itself to be a relevant factor between graduate and post-graduate levels of education of managers. Recalling we combined PhD with master's degree to obtain post-graduate category due to PhD's small pool of respondents, combined groups of education reported statistical insignificance at target constructs. However, while doing so we realized that if taken separately as a category, when educational degree reaches out to PhD level, there is clear evidence that managers adopt to GAI, utilize it to improve their managerial tasks, at the same time they undergo more stress about the possibility of replacement. combined groups reported statistical insignificance. This opens great space for further analysis.

We know from the literature that education has a positive relation with skill evolution (Author & Prince, 2013). If we consider adapting to GAI is solely dependent on skill evolution of managers, we can argue that our findings are against the literature. A reason why we didn't find a statistically significant relationship across education levels is that managers might have undergone similar educations. A strong embracement of skill evolution might already set ground even at the graduate level. Hence, in advanced universities people are motivated and knowledgeable enough to adapt, utilize and be confident with technological changes not depending on educational levels. Regardless, Performance Increase with GAI, Technostress by GAI, or Willingness to Adapt to GAI didn't report strong relationship with diploma.

5.2 Analysis for Managerial Roles

Recall that we have divided nature of managerial work into two categories: Interaction with other people and automative nature of tasks. We aimed to reveal whether managers at different occupations responds differently to our constructs. After conducting series of regression and variance tests we found no statistical significance in between managers for target constructs. This indicates that occupation categories that we provided **(see table 7)** are not in a significant relation between each other across Performance Increase with GAI, Technostress by GAI, and Willingness to Adapt to GAI.

We hypothesized that there will be significant differences across interaction and automation levels of managerial tasks. This statistical insignificance prevented us to reject null hypothesis for $\mathbf{H_{2a}}$, $\mathbf{H_{2b}}$, $\mathbf{H_{3a}}$, $\mathbf{H_{3b}}$, and $\mathbf{H_{3c}}$. Directions of categories they still remain unknown since we didn't test further after receiving statistical insignificance and it was hard to comment on just by examining roles regression where we regressed each occupation for CEO. We can conclude that automation and interaction categories of managers, as well as different jobs by themselves did not provide a statistically significant relationship for their target constructs. It was exceptionally surprising for us.

For Technostress construct, when we look at mean averages for constructs taken from survey questions, we observe is managers reported slightly higher than neutral (3), recall that answers are given in 1-5 Likert format. Combining these two together, we argue non-interactive and highly automative job (where we expected to have highest points of Technostress) holders undergo stress as much as the opposite (highly interactive – low automation) holders. This might be happening because of the freshness of GAI that needs time to be internalized before producing stress of replacement. We are still at the very beginning of job transformations with GAI; therefore managers might still feel confident with their positions and they could are not bothered by the possibility of their jobs transform in away that heavy GAI usage becomes a necessity. Hence, the magnitude of GAI effect needs to be expanded into managerial tasks further before we find significant relationships between stress and different managerial jobs. At the same time, there is a general increase in stress levels in Turkey, therefore the marginal stress effect of incoming GAI might not be as strong as we expected.

We also notice that mean averages for improvement at performance construct point out below three in the Likert Scale, meaning that managerial task performance improvement isn’t perceived as strong for managers as we expected. Same can be said for willingness to adapt to GAI too while it being slightly higher than three.

We know that for certain tasks, such as drafting papers, writing codes, market research etc., GAI proved itself quite useful. We observe that managers at different departments reported that they are not experiencing performance increases with GAI or performance increase with GAI at all (regarding Likert scale is around 3 – Neutral). We reason that, recalling financial managers, they couldn’t enjoy portfolio management with GAI since the technology is available for all the managers and it became a necessity instead of a competitive edge. This might be the case for our surveyed managers. Majority of the industry is taking advantage of GAI might have created a hesitation since it turned expertise at such tasks the new normal.

Another argument could be that, recalling the problems of GAI and its adaptation / use, managers might still be hesitant of its application within their profession and not enjoying the possible improvement regardless of the job’s automative or interactive nature.

On the other hand, this could be a result of something positive. We would expect managerial duties that require high interaction can’t enjoy GAI as non-interactive and more technical ones, yet they also report GAI being not effective enough to make a difference. We comment on this finding that, GAI and its tools might be as affective for interactive tasks as they for non-interactive technical duties of managers, hence a significant difference doesn't exist.

Regardless, recalling Slonim, (2018), we believe a fundamental underlying reason why managers did not report a behavioral change with the introduction of GAI is the superior balancing factor of humans compared to GAI. As literature suggests, managers are still outperforming GAI at distinguishing errors for certain tasks, our mind has a strong understanding of multi factorial reality which can be unseen by GAI since it has an expertise at particular tasks, not by considering multiple factors as much as we do. This situation is also discussed at concerns with GAI section. Based on this, managers might still be hesitant to implement GAI at their work, they might be considering that it is not yet developed enough to help them at their tasks.

Second element is from Agrawal, (2018) where we discussed that managerial work is still too complex. Regardless of the functions and hierarchical responsibilities within the pyramid of duties, we see that majority of managerial tasks are still too complex, requires high level of interaction and complex decision making even with tasks that are relatively less crucial. Even administrative tasks still require human presence at a high level and GAI has not yet evolved so that we observe a report from managers.

One last argument that can bring here is that the possibility of unfamiliarity. Although GAI is the next big thing, its applications might not be present for everyone who wants to train themselves. Meaning that orientation for GAI could still be absent for managers to take advantage of it. This situation might create a time requirement for managers to adopt into GAI and enjoy its capabilities.

To conclude discussion, our own findings imply a state of status-quo where we don't observe a high interaction of managers and they are hesitant to utilize the technology. At the same time, we know that in certain industries firms with high exposure to GAI outperformed firms with lower exposure, moreover, GAI is already being used in accounting, screening candidates, market research, etc. Our findings do not support the positive predictions of GAI use on managerial behavior change, yet we know that sooner or later this technology will be the future of not only managerial tasks, but many tasks around world. It might not be the correct time so that we see a strong influence from managers across the world, yet this doesn't imply that the change is not happening.

5.3 Managerial Implications

Key findings of our analysis were:

- With the introduction of GAI, managers experience technostress more than improvement at their tasks and their willing to adapt to GAI. Still, the findings are around neutral in the Likert Scale, indicating that we don't observe a strong effect came with GAI in managerial behaviors.
- Demographics like gender, degree of education and firm are irrelevant at influence consideration regarding managerial behavior change.
- Roles with different tasks that could be automated by GAI nor their level of interaction with people did not present itself to be significant at improvement of tasks, stress level and adaptation metrics.

5.3.1 Interaction and Automation of Tasks Don't Cause Managers to Utilize GAI

We understand that the introduction of GAI might not necessarily nurtured a positive and clear impact on managerial behavior. Nevertheless, one must not forget that we are still at the introduction stage and GAI tools are ever developing. Based on our findings, we recommend that organizations should adopt a holistic approach that treats managers across different levels of hierarchy and different work natures together at this point in time. The distinguishment doesn't prove itself to be effective, therefore role-specific technology integration isn't recommended. Organizations should understand where the potential is highest if GAI is integrated and create a tasks specific training and adaptation strategy, hence, train managers based on an organizational goal all together.

A further note here is that, since managers do not report improvement at their tasks across functions, it may be because of their unfamiliarity with the capabilities. Organizations can acknowledge this situation and promote cross-functional discussion groups. In these groups, managers can discuss the new tools and how other managers across the world utilizing the technology. In short, share the expertise and develop an organizational knowledge and look for across functional inspiration.

5.3.2 Perceived Stress at Managerial Behavior Change with GAI

Although the findings do not imply a strong stressful situation, overall mean values were higher at C2, therefore, organizations should be aware of that managers will feel the stress of replacement before they feel the benefits of GAI and before their urge to for developing themselves with evident GAI-related skills. Organizations might want to be attentive to this situation and develop recurring surveys that measures technostress levels of managers that technological advancements bring. Moreover, when the stress levels are measured at a significant level, role specific trainings could be considered that trains the staff about relevant tools of GAI and how they can get performance improvements with those tools. Note that, any behavioral change at the global level will take time to present itself evident across locations.

5.4 Limitations

This study, conducted in a centralized location such as Turkey, encountered several limitations that warrant consideration. Firstly, the sample size of 50 participants may be deemed relatively small, raising concerns about the generalizability of the results to larger populations. Although efforts were made to ensure diverse representation within the sample, caution should be exercised when extrapolating the results to broader and more heterogeneous populations. It was a valuable insight to see there might be an underlying relationship between education and utilization of GAI at the PhD level, however, further room with better respondent population is well encouraged.

Another notable limitation arises from the probability of mistakenly evaluating the nature of occupations. The categorization of professions based on their interactive and automatic nature constituted a critical aspect of the study's framework. However, subsequent analysis revealed statistical insignificance concerning the formulated hypotheses. Naturally, this makes us consider the potential room for growth of our categorizations. GAI technology is subject to change in a daily manner; therefore, these categorizations are constantly moving towards the ground where GAI has the authority to perform better than managers. Yet, at this point of the time might be too early to categorize them in the way we presented. It is also a possibility that we might not adequately captured the essences of occupational attributes, and it might lead us to have differences between the perceived categorizations and the actual nature of those occupations.

An additional concern is that the underlying construct in the survey is retrieved from EFA method, while this is generally accepted, the limitations of EFA method should also be considered. We acknowledge that there is a room for improvement regarding our survey questions, such that they might not be enough to gather information about our questions, moreover, our constructs might not be adequate to capture the essence of underlying reasoning between managerial behavior change and introduction of GAI. We invite researchers for further development.

To summarize, the limitations are location, modest sample size, potential miss grouping of managerial roles and miss creation of constructs, as well as the limited ability of conducted tests to reveal underlying phenomena. There is also room for growth regarding the comprehensiveness of survey questions and constructs. We invite academics to exercise caution when applying these results and recommendations into their arguments, especially if they are outside Turkish context, and recall the room for further research to acquire more refined, comprehensive, and reliable picture of the interactions between GAI and managerial behavior change.

5.5 Suggestions for Future Research

Based on our findings, we detected great space for future research which could contribute to a deeper understanding of managerial behavior change with GAI. The dynamics between the nature of managerial roles, capabilities of GAI and how they interact with each other is a vast topic to investigate. We present the following suggestions to point out direction in case of further research:

Impact of Vice Manager Adoption on Employee Utilization of GAI:

We believe there is a connection between Vice managers' adoption of General AI extends further of their personal development and creates a motivation for their functions to adapt into GAI at a higher pace. Thus, we believe that this adoption will generate positive results for organizations. The assessment can be about two groups, one with a Vice manager who utilizes GAI, and the other is without it. Then, employee responses can be collected to understand each groups' utilization and perception of GAI.

Exploring the Correlation Between Interactive Nature of Work and Monitoring

Recall that we introduced monitoring as a base responsibility for every manager, emerging from the managerial task pyramid. We recommend further analysis of the possible relationship between the monitoring and whether jobs that require monitoring could be classified as jobs with high level of interactive nature. We believe that part of monitoring requires personal connections yet without an analysis this is difficult to comment on. We note that, understanding interactive nature of the work at a further extent would help researchers to better classify managerial duties and eventually they will have a better base to make predictions about the impact that GAI brings.

Expand Comparative Analysis Across Managerial Roles

Conduct comparative analyses across different industries and organizational sizes to reassess variations in the impact of GAI adoption on managerial behavior change. This will enable researcher to recommend on whether managerial roles indeed effect the change at managerial behavior and adaptation to GAI relation.

Longitudinal Studies on GAI Integration

Undertake longitudinal studies to track the evolution of GAI integration in managerial roles over time. Assess how managers' use of GAI technologies evolves, and whether managers' report a change in their way of performing managerial duties follows a similar trajectory. Longitudinal studies could provide insights into the projection of GAI adoption.

We believe with these studies there will be a better base for managerial nature of the work discussion, which will enable us to better classify managerial duties and inspect whether GAI has a significant relationship with these roles and whether we see a transformation in the way of performance regarding these tasks. We note that, expanding the academic discourse and cumulate the data will be enlightening for further researchers navigating the managerial role change and GAI impact on it.

Paradox Theory and Change in Employment Market

We believe that Paradox Theory might enlighten researchers to understand whether the foreseen effects of GAI in the job market and managerial behavior change. As theory suggests, automation will bring further augmentation, therefore the job market might not be a subject to major changes regarding managerial environment.

5.6 Concluding Remarks

This study found that the managers across different genders, different levels of education, different firm sizes and roles did differ statistically significantly in terms of target constructs. Between the categories of interaction and automation at managerial work, across their levels from high to low we also did not find a statistically significant relationship. Future studies might consider investigating managerial titles and how they are reacting to GAI with better datasets and constructs to obtain a more generalizable conclusion of the impact of GAI on managerial behaviors.

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Appendix A

Tables

Table 1

Possible GAI Applications in Different Management Fields for Business

Possible GAI Applications in Different Management Fields for Business					
Marketing Management	**Operation Management**	**IT Management**	**Risk Management**	**HRM**	**Employee Management**
Marketing and sales content generation for social media marketing	GPT for customer feedback	Writing code for software	Drafting of risk guidelines	Assisting interview questions and assessment of candidates	Optimizing employee communications
Product usage guidelines	Error identification and troubleshooting	Autogeneration of contextual information	Summarizing changes	Providing HR functions digitally	Creating business presentations
Customer feedback and planning	Streamlining customer service	Generation of synthetic data	Answering questions for risk documents		Synthesizing summaries
Salesforce training manual generation	Identifying interest in leveraging a comparative advantage				Enabling search and question answering
Chatbot support for advertising and sales					Automation for document preparation

Note. From "How to Bell the Cat? A Theoretical Review of Generative Artificial Intelligence towards Digital Disruption in All Walks of Life" by Mondal et al., 2023, *Technologies 11 ,*44*,* p. 8 (https://doi.org/10.3390/ technologies11020044). Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland

Table 5

GAI Deployment and Total Value Potential Across Selected Industries

Generative AI could deliver significant value when deployed in some use cases across a selection of top industries.

Selected examples of key use cases for main functional value drivers (nonexhaustive)

Value potential of function for the industry: – High – Low

	Total value potential per industry, $ billion (% of industry revenue)	**Value potential,** as % of operating profits[1]	**Product R&D, software engineering**	**Customer operations**	**Marketing and sales**	**Other functions**
Banking	200–340 (3–5%)	9–15	**Legacy code conversion** Optimize migration of legacy frameworks with natural-language translation capabilities	**Customer emergency interactive voice response (IVR)** Partially automate, accelerate, and enhance resolution rate of customer emergencies through generative AI–enhanced IVR interactions (eg, for credit card losses)	**Custom retail banking offers** Push personalized marketing and sales content tailored for each client of the bank based on profile and history (eg, personalized nudges), and generate alternatives for A/B testing	**Risk model documentation** Create model documentation, and scan for missing documentation and relevant regulatory updates
Retail and consumer packaged goods[2]	400–660 (1–2%)	27–44	**Consumer research** Accelerate consumer research by testing scenarios, and enhance customer targeting by creating "synthetic customers" to practice with	**Augmented reality–assisted customer support** Rapidly inform the workforce in real time about the status of products and consumer preferences	**Assist copy writing for marketing content creation** Accelerate writing of copy for marketing content and advertising scripts	**Procurement suppliers process enhancement** Draft playbooks for negotiating with suppliers
Pharma and medical products	60–110 (3–5%)	15–25	**Research and drug discovery** Accelerate the selection of proteins and molecules best suited as candidates for new drug formulation	**Customer documentation generation** Draft medication instructions and risk notices for drug resale	**Generate content for commercial representatives** Prepare scripts for interactions with physicians	**Contract generation** Draft legal documents incorporating specific regulatory requirements

[1]Operating profit based on average profitability of selected industries in the 2020–22 period.
[2]Includes auto retail.

Note. From "The Economic Potential of Generative AI. The Next Productivity Frontier by Chui et al., 2023, p. 26. Copyright © McKinsey & Company.

Table 7

Demographics

Variable	**Sample Size**	**Percentage**
Job Positions		
Team Leader	5	10%
CEO	10	20%
Production Manager	5	10%
Sales Manager	9	18%
Marketing Manager	10	20%
Law Manager	2	4%
HR Manager	9	18%
Total	*50*	*100%*
Firm Size		
1 - 50	14	28%
51 - 200	9	18%
201 +	27	54%
Total	*50*	*100%*
Gender		
Male	35	70%
Female	15	30%
Other	0	0%
Total	*50*	*100%*
Degree of Education		
High School	1	2%
Bachelor’s	30	60%
Master’s	17	34%
PhD	2	4%
Total	*50*	*100%*

Appendix B

Figures

Figure 4

Change in Monitoring Employees at Legal Departments

Change in Monitoring Employees at Legal Departments	
Traditional Way	**Application of GAI**
Supervising legal research and document review manually	AI-powered legal research tools can enhance monitoring by automating routine tasks, allowing managers to focus on more complex legal issues. AI algorithms can assist in tracking changes in laws and regulations.

Figure 5

Change in Motivating Employees at Law Departments

Change in Motivating Employees at Law Departments	
Traditional Way	**Application of GAI**
Verbally acknowledging lawyers for successful case outcomes, client satisfaction, or exceptional legal research	For instance, a lawyer successfully navigating a complex legal issue may receive real-time acknowledgment from the AI system. Simultaneously, the system might recommend specialized training to further enhance skills in a related legal domain.

Figure 6

Change in Motivating Employees at Finance Departments

Change in Motivating Employees at Finance Departments	
Traditional Way	**Application of GAI**
Recognizing financial achievements and promotions	AI can optimize financial processes, improving efficiency and accuracy. Managers can motivate teams by highlighting the strategic impact of their work and facilitating professional growth through AI-supported training

Figure 7

Change in Monitoring Employees at Finance Departments

Change in Monitoring Employees at Finance Departments	
Traditional Way	**Application of GAI**
Overseeing financial transactions and manually reviewing reports	AI can automate transaction monitoring, detect anomalies, and ensure compliance. Managers can focus on strategic financial planning, while AI handles routine tasks.

Figure 8

Change in Motivating Employees at Sales Departments

Change in Motivating Employees at Sales Departments	
Traditional Way	**Application of GAI**
Setting sales targets and providing incentives based on achievements	AI-powered sales coaching tools can offer personalized feedback and guidance, boosting motivation. AI algorithms can also assist in tailoring incentive programs based on individual strengths and weaknesses

Figure 9

Change in Monitoring Employees at Sales Departments

Change in Monitoring Employees at Sales Departments	
Traditional Way	**Application of GAI**
Reviewing sales reports and manually assessing performance	AI analytics tools can monitor and analyze sales data in real-time, offering insights into individual and team performance. Predictive analytics can help identify potential challenges and opportunities.

Figure 10

Change in Monitoring Employees at Marketing Departments

Change in Monitoring Employees at Marketing Departments	
Traditional Way	**Application of GAI**
Managers traditionally track the number of tasks completed or campaigns launched by each marketing team member	AI tools can monitor campaign performance in real-time, providing instant insights. Managers can leverage AI-generated reports to make data-driven decisions and allocate resources more effectively.

Figure 11

Change in Motivating Employees at Marketing Departments

Change in Motivating Employees at Marketing Departments	
Traditional Way	**Application of GAI**
Recognizing successful campaigns and providing creative freedom	By automating routine and repetitive marketing tasks through AI, employees are liberated from mundane activities. This gives them the freedom to channel their energy and creativity into more meaningful and innovative aspects of marketing campaigns

Note for Figure 4-11; Source: Author's perception.

Figure 14

Managerial Roles and Improvement at Performance Box Plot

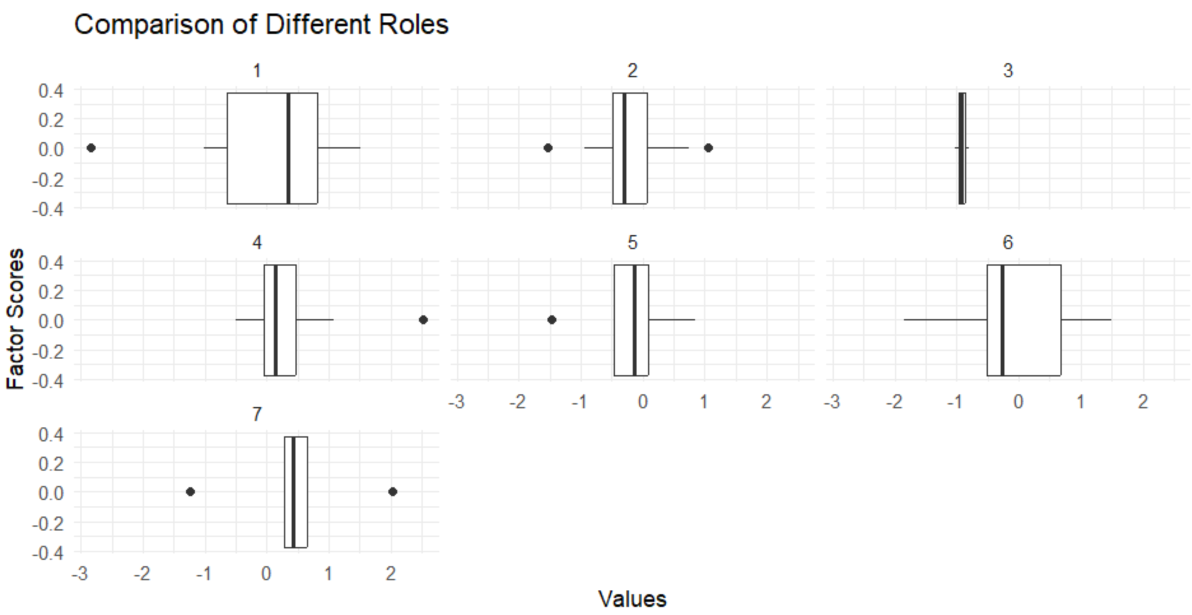


Figure 15

Managerial Roles and Technostress Box Plot

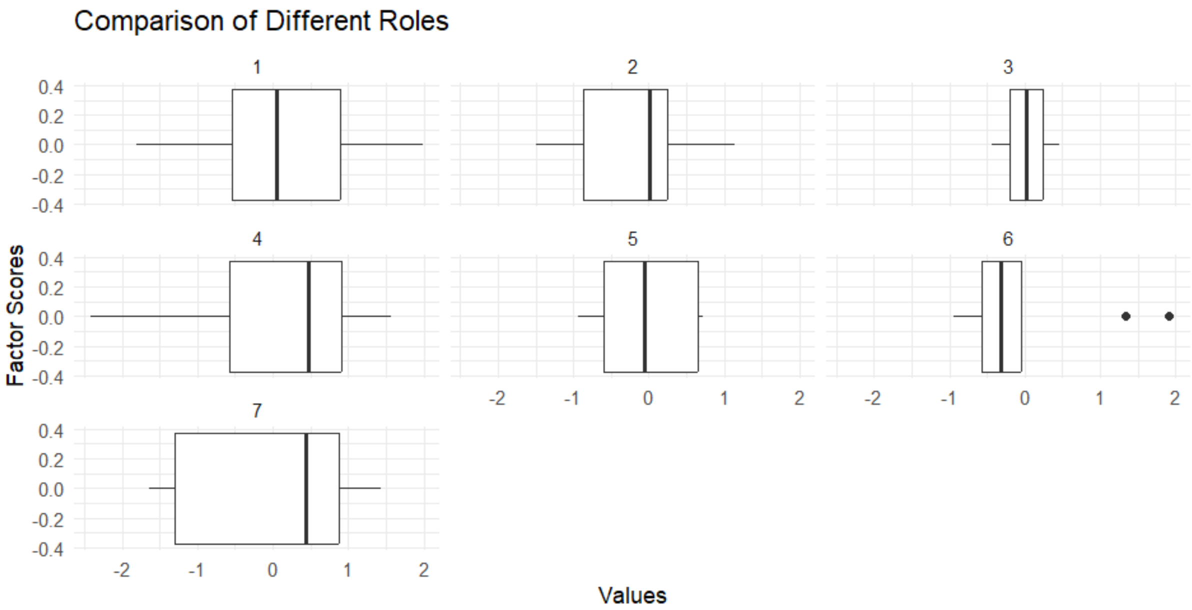


Figure 16

Managerial Roles and Construct 3 Box Plot

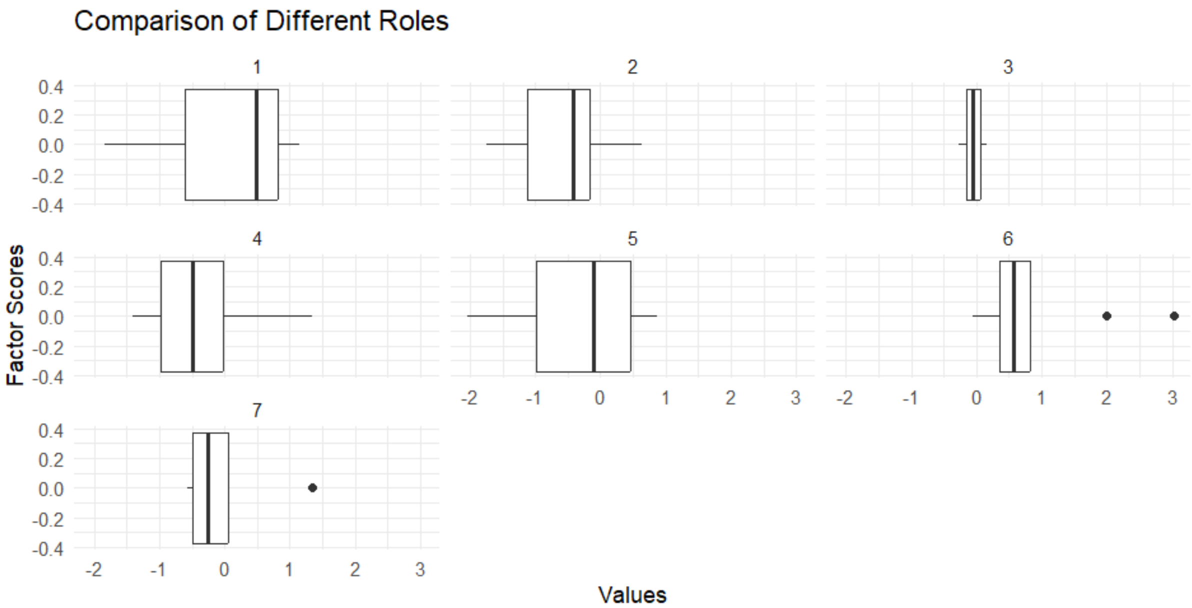
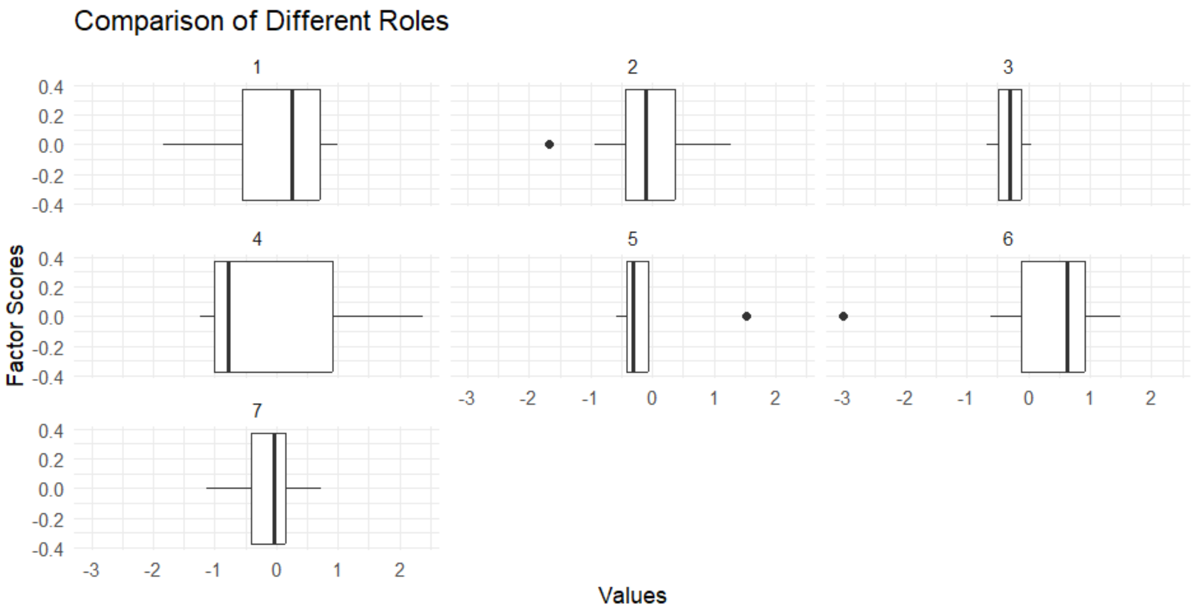


Figure 17

Managerial Roles and Willingness to Adapt to GAI Box Plot



Note for figure 14-17; Source: R