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Artificial Intelligence Integration in Multinational Corporations: Impacts on Operational Efficiency and Workforce Dynamics

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Abstract

The study focuses on the adoption of Artificial Intelligence (AI) in the organizations, especially the multinationals, and its effect on operational efficiency and employee relations. A quantitative methodology was used through a structured questionnaire, which was applied to employees who work in organizations that already have AI. The data were collected using a cross-sectional survey and analyzed using a combination of descriptive and inferential methods such as correlation and regression analysis.

The results indicate that the use of AI in daily work is now relatively common and is closely associated with improved productivity, efficiency and decision making. The majority of employees believe AI is a good tool that enables them to do better and provide results for the organization. The findings, however, suggest at the same time that AI is more likely to be associated with a change in job roles rather than direct job loss. Employees report greater task automation and also a shift to more complex, value-adding work.

But the picture is not wholly one-sided. While the overall perspective is positive, there are still some concerns around job security and the transparency of AI systems. Trust in AI is relatively high, but employees are not very sure about how these systems actually produce their outputs. Regarding Trust a very important thing is the support provided from the organization and how AI is being integrated to the everyday work. Managerial encouragement and access to digital upskilling opportunities seem to have a clear impact on the use and perception of AI.

The study aims to offer a more holistic understanding of AI adoption in modern organizations by taking also into account both the company's performance and employees' perspectives. The results suggest that successful deployment is not just about technology, but how it fits into organizational structures and employee needs, particularly in more complex multinational environments.

Keywords

Artificial Intelligence (AI), Digital Transformation, Multinational Corporations, Operational Efficiency, Workforce Transformation, Employee Perceptions

Περίληψη

Η παρούσα μελέτη σχετίζεται με την ενσωμάτωση της Τεχνητής Νοημοσύνης (AI) σε πολυεθνικές επιχειρήσεις, και εξετάζει πώς αυτή επιδρά όχι μονο στην αποδοτικότητα της επιχείρησης αλλά και στη δυναμική του ανθρώπινου δυναμικού. Η έρευνα βασίζεται στα αποτελέσματα του ερωτηματολογίου που συμπλήρωσαν οι εργαζόμενοι των επιχειρήσεων στις οποίες εφαρμόζεται και χρησιμοποιείται η AI. Τα αποτελέσματα συγκεντρώθηκαν και μελετήθηκαν μέσα από περιγραφικές και επαγωγικές στατιστικές μεθόδους, όπως για παράδειγμα συσχετίσεις και παλινδρόμηση. Τα συμπεράσματα μας δείχνουν ότι η AI μπορεί να ενσωματωθεί στην καθημερινή εργασία και συνδέεται άμεσα με υψηλότερη παραγωγικότητα, μειωμένο χρόνο διεκπεραίωσης εργασιών και βελτίωση στη λήψη αποφάσεων. Βάσει των απαντήσεων του ερωτηματολογίου, φαίνεται ότι οι εργαζόμενοι αντιμετωπίζουν την AI σαν ένα εργαλείο που βελτιώνει την απόδοσή τους και τον τρόπο εκτέλεσης της εργασίας. Επίσης, παρατηρείται ότι η AI μετασχηματίζει χωρίς να αντικαθιστά τις θέσεις εργασίας, διότι ενώ αυξάνει την αυτοματοποίηση απλών εργασιών, οδηγεί τους εργαζόμενους να επικεντρώνονται σε υψηλότερης αξίας δραστηριότητες.

Ωστόσο, παρά τη θετική στάση των εργαζομένων προς την AI, δεν μπορούμε να παραβλέψουμε τον προβληματισμό τους ως προς την ασφάλεια της εργασίας τους και την κατανόηση του τρόπου λειτουργίας των νέων συστημάτων. Η πολιτική της επιχείρησης πρέπει να βασιστεί στην ψηφιακή αναβάθμιση των δεξιοτήτων των εργαζόμενων για να τους οδηγήσει σε μία θετική αντιμετώπιση ως προς την υιοθέτηση της AI.

Αυτή η μελέτη συνδυάζει την οπτική της επιχειρησιακής απόδοσης με την προσωπική εμπειρία των εργαζομένων ώστε να καταλήξουμε σε μία ολοκληρωμένη εικόνα της χρήσης της AI. Τα αποτελέσματα δείχνουν ότι για να αποδώσει η εφαρμογή της AI τεχνολογίας είναι απαραίτητο να «ταιριάζει» τόσο με τον τρόπο που είναι οργανωμένη η εταιρεία όσο και με τις ανάγκες των εργαζομένων, κάτι που είναι ακόμη πιο σημαντικό στις πολύπλοκες πολυεθνικές επιχειρήσεις.

Λέξεις – Κλειδιά

Τεχνητή Νοημοσύνη (AI); Ψηφιακός Μετασχηματισμός; Πολυεθνικές Επιχειρήσεις; Επιχειρησιακή Αποδοτικότητα; Μετασχηματισμός Εργασίας; Αντιλήψεις Εργαζομένων

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List of Abbreviations & Acronyms

Abbreviation / Acronym	Full term
AI	Artificial Intelligence
MNCs	Multinational Corporations
ERP	Enterprise Resource Planning
CRM	Customer Relationship Management
RPA	Robotic Process Automation
RQ	Research Question
H	Hypothesis
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
GDPR	General Data Protection Regulation
SPSS	Statistical Package for the Social Sciences
IBM	International Business Machines
IT	Information Technology
HR	Human Resources
Std. Deviation	Standard Deviation
df	Degrees of Freedom
Sig.	Significance
Asymp. Sig.	Asymptotic Significance
ANOVA	Analysis of Variance

1 INTRODUCTION & RESEARCH FRAMEWORK

1.1 Background of AI in Global Business

The rise of AI in global business is not happening in isolation. It is part of a much bigger shift associated with digital transformation. However, in most organizations, AI does not come as a standalone innovation but as something that grows with the shift in processes, data systems, and decision-making practices. Time has passed and companies are beginning to leave behind the use of disconnected digital tools, and move toward more integrated systems, where data can flow more freely across departments. This makes the operations more coordinated and more responsive in many cases. In that sense, AI is less about replacing existing systems, but about becoming part of how organizations gradually evolve on structural level (Verhoef et al., 2021).

At the same time, it is more and more obvious that AI is no longer confined to trial phases or isolated projects. In most organizations, AI is already a part of daily work. Employees regularly use AI tools, and very often rely on them to get tasks done faster and in a more accurate way. Employees tend to use AI tools due to the usefulness of these systems, especially in terms of time savings or productivity gains. The strategy the company will decide to follow in order to smoothly integrate AI plays a vital role. When there are visible managerial support or opportunities for digital upskilling, employees seem more willing to engage with AI tools. This implies that the adoption of AI is not considered as an optional activity but is increasingly integrated into regular working processes and aligned with wider organizational priorities (Brynjolfsson et al., 2025; Venkatesh et al., 2012).

However, that doesn't mean the experience is the same for everyone. Even within the same organization, there could be quite a variation in how much interaction there is with AI. Some employees prefer to use it frequently as part of their daily work, while others use it only under specific circumstances. This can be explained by differences in job profiles, access to tools or simply by the comfort individuals have with digital technologies. The situation becomes more complicated in multinational corporations. These organizations are spread across several countries, each with their own market conditions, regulations and cultural expectations. Therefore, to achieve a successful AI adoption, it requires coordination between teams that are geographically dispersed, and careful consideration of local requirements. As a result, companies often try to find a balance between standardization, which means using the AI systems everywhere and local adaptation, so that each country or team has enough flexibility to adjust the system to their own needs (Bughin et al., 2018; Mikalef & Gupta, 2021).

In practice, this balance is not always easy to achieve. On the one hand, standardized AI tools can increase consistency and make processes more efficient. On the other hand they do not always fit easily with local ways of working. This creates a situation where AI is asked to do two things at once, to bring everything together and at the same time to allow for differences where needed.

This creates a rather dual role of AI in multinational environments. It enables the integration of operations through common platforms and data structures but also requires organizations to remain agile and to adapt to local realities. More generally, it is indicative of a change in the way companies deal with technological change. AI is used not only to improve efficiency, but also to handle complexity, manage cross-border operations and respond to changing business environments. In this sense it is not only a matter of technical possibilities but also begins to matter how global business is actually organized and done.

1.2 Research Problem & Rationale

The expanding use of AI within organizations has brought to the forefront an unresolved tension: the relationship between productivity gains and the potential disruption of the workforce. AI is frequently associated with obvious operational gains such as faster execution times, increased accuracy, and more informed decision making. But the adoption of AI also raises concerns around job transformation, the risk of skills becoming outdated and longer-term employment stability. These two dynamics are not independent. Instead, they tend to unfold together within the same organizational settings, often shaping employees' thoughts and responses to AI in ways that are not always straightforward (Brynjolfsson et al., 2025; Acemoglu & Restrepo, 2020).

Findings from present study appear to reflect on this complexity. Many employees can recognize the practical benefits AI usage can provide to them, particularly in terms of efficiency improvement on helping them with day to day tasks. However, there is an important amount of concern about how these changes might impact their future roles. However, these concerns do not seem to provoke strong resistance. Rather, they coexist with relatively high levels of trust, continued use, and generally positive attitudes toward AI supported work. This could suggest that workforce disruption is viewed not as a threat which will replace workers, but rather something more gradual, less about short-term job loss, and more about a continuing, and more ambiguous role transformation (Glikson & Woolley, 2020).

Despite the rapid growth of research on AI in organizations in recent years, it still feels a little fragmented. Most studies tend to focus either on performance-related outcomes, like efficiency and productivity, or on labor-related concerns such as automation and employment risks. What is less common is a research that looks at both sides together in the same context. Consequently, the knowledge around how these two dimensions interact in practice, particularly in terms of day to day work and the employee experience, can be considered limited. The absence of such integration in literature prevents a holistic understanding of what AI adoption actually entails within organizations, beyond high-level outcomes (Raisch & Krakowski, 2021).

This gap is even more significant when examining multinational corporations. The MNCs face a greater degree of complexity than smaller or more localized firms. They work in different countries, governance systems and cultural environments and the composition of their workforce is often diverse in structure and expectations. Under these circumstances, the adoption of AI is not simply a matter of deploying new tools. Larger issues like coordination, governance and cross-border alignment are also at risk. Thus, multinational companies provide a particularly informative context to investigate the impact of AI on performance outcomes and employee experiences simultaneously (Jöhnk et al., 2021).

Focusing on MNCs, this study is able to capture a more holistic picture of AI-related change. These organizations combine efficiency pressures, technological integration and workforce adaptation in both visible way and ongoing processes. At the same time it is important not to assume that these processes are always smooth or fully aligned. Improvements in productivity in many cases may come with trade-offs, especially from the employee's perspective. By examining these dynamics side by side, the study moves beyond the simple question of whether AI is beneficial or disruptive, and instead explores how these effects occur simultaneously within complex organizational environments.

1.3 Research Aim & Objectives

The aim of this research is to investigate the application of AI in multinational companies and its impact on operational efficiency and employee perceptions. More specifically, the research investigates the implications of AI enabled systems for everyday organizational processes, decision-making practices and employee role formation in a contemporary corporate setting.

To achieve this, the research considers AI as not just a means to greater efficiency, but as an agent that can gradually change the nature of work. And at the same time, AI technologies are increasingly embedded into business operations, helping to automate, increase productivity and improve decision making. The flip side is that more of these systems mean more questions about how jobs are being redesigned, what skills are becoming more or less important, and how employees actually feel about working with these systems. In this context, the issues of trust, resistance and job security concern become hard to ignore.

The study is therefore guided by the following objectives:

- To investigate the extent of integration of AI into everyday work processes in multinational organizations
- To quantify employee perceptions of the impact of AI on operational efficiency, such as productivity, accuracy and decision making
- To investigate the level of impact of AI on job roles, task design, and required skills
- To better understand employee perceptions of AI, particularly with respect to usefulness, ease of use, trust, and potential resistance

- To examine the relationship between the use of AI, organizational performance and employees' attitudes towards technological change

By addressing these areas, the study seeks to provide a more realistic understanding of what actually happens in AI adoption. It aims to understand the simultaneous experiences of efficiency gains and the changing nature of work in multinational corporate environments instead of looking at the results in isolation.

1.4 Research Questions / Hypotheses

Guided by the above aim and objectives, the study is challenged to answer the following research questions:

- **RQ1:** To what extent is Artificial Intelligence embedded in the processes of multinational corporations?
- **RQ2:** What is the effect of AI integration on perceived operational efficiency in terms of productivity and decision-making effectiveness?
- **RQ3:** What is the impact of AI adoption on workforce dynamics, particularly on job roles and task automation?
- **RQ4:** What do employees think of AI in terms of usefulness, ease of use, trust, and possible risks?
- **RQ5:** How do employee attitudes towards technological change and AI usage relate to each other?

To deal with these problems in a more systematic way, the study also suggests a set of hypotheses:

- **H1:** AI use has a positive relationship with perceived productivity and overall operational efficiency
- **H2:** The use of AI is positively associated with the effectiveness of decision-making
- **H3:** AI use is positively associated with job transformation and task structure changes
- **H4:** Employee acceptance of AI is positively influenced by perceived usefulness and ease of use

- **H5:** Trust in AI systems has a positive influence on employees' willingness to adopt AI systems
- **H6:** Fear of job displacement has a negative effect on AI acceptance

Together, the research questions and hypotheses provide a structured way to approach the empirical analysis. At the same time it is worth mentioning that real organizational environments are often more complex than pre-defined hypotheses can capture in full. This is why the study does not view these relations as fixed, but as a starting point to understand how the adoption of AI is being experienced in practice, based on the survey and the data collected.

1.5 Scope & Delimitations

The study explores the experience of AI in organizations, focusing on firms where these systems are already embedded in daily operations. Instead of an abstract notion, AI is considered here in practical terms: systems which use data to perform tasks that typically require human judgement, such as pattern recognition, prediction or decision-making support (Raisch & Krakowski, 2021). Meanwhile, the discussion is placed in the broader idea of digital transformation, which refers to the more gradual but far reaching change companies go through as they integrate digital technologies into their core operations. This shift often changes the way work is done, but also the organizational structure and the value creation (Verhoef et al., 2021).

The emphasis on multinationals and large scale organizations is deliberate. AI is rarely adopted on an ad hoc basis in these environments. More often, it is associated with broader strategic priorities. For example, multinational corporations work in more than one country, and they need to comply with a number of regulatory systems, cultural backgrounds and operational needs. And that adds another layer of complexity that makes AI implementation particularly interesting. On the one hand, there is a need for consistency and standardization across the organization, on the other hand, local adaptation is still required (Jöhnk et al., 2021). And in this tension lies many of the practical challenges, and opportunities, of AI adoption.

Despite this clear focus, there are some limitations of the study that should be acknowledged. The data were collected using a cross-sectional survey, meaning employee views at one point in time. As such, it does not address how perceptions or experiences of AI might change, which is especially relevant in light of the rapid pace of change of these technologies, and of organizations' responses to them. So they reflect the way employees make sense of and evaluate their experiences, rather than providing an objective perception of organizational outcomes.

There are also limitations in the collection of the sample. Convenience and snowball sampling facilitated the reaching of the participants, meaning that the sample cannot be considered as fully representative of all AI-enabled organizations. The results should therefore be reviewed with some caution. Finally, the study is not focused on particular organizations or industries. It steps back, and looks at broader patterns across different, anonymized contexts instead. This restricts the detail of any one case but allows a more general view of how AI is being integrated across organizational settings. All these choices together define the scope of the study, while still being coherent with the general research direction.

1.6 Structure of the Dissertation

The dissertation is divided into six chapters. While these chapters are presented as separate sections, they are directly connected with each building on the previous one.

It starts with the introductory chapter, which is basically setting the scene. Here we focus on why the study of AI in global business is worthy of attention and how the topic fits into larger organizational changes. The research problem is also defined with the purpose and main questions, so it provides clear directions from the beginning and not something that appears later on.

Then the discussion turns to the review of the literature. This section attempts to bring together various strands of research, in order to illustrate how AI has been approached so far in business contexts. The multinational corporations get a lot of attention as it is a more complex setting. The chapter also discusses issues such as efficiency, change in the workforce and employee perception. Some of the literature is not completely aligned and this is actually more useful in pointing out where the gaps are. The conceptual framework does not seem to be a separate entity but develops gradually from this discussion.

In the third chapter we pass to more practical matters and describe how the research was made. The emphasis here is not simply to list methods but to explain the rationale behind the choices made, including research design, data collection process and approach to analysis.

Then the emphasis falls on the data themselves. The findings chapter presents the results of the survey. It begins with more general patterns and then moves on to the statistical analysis. The main aim at this point is to show what emerged from the data, even if some of the results are not completely expected.

In the following chapter we try to interpret these results. In this section the results are discussed in the context of existing literature. While some of the findings are consistent with what has already been suggested in previous studies, others seem to point in slightly different directions. This part also has some practical implications especially for organizations dealing with AI adoption in different contexts.

Finally, the dissertation ends by tying everything together. It comments on the principal points that have come out, but also notes the limitations that should not be overlooked. It also highlights where more research may be needed, given how quickly the topic itself is evolving.

2 LITERATURE REVIEW: AI IN CORPORATE ENVIRONMENTS

2.1 Evolution of AI in Business Operations

AI in business operations hasn't really happened as one distinct, singular shift. It is best understood as a gradual process, where different types of technology have been layered on top of each other over time. Earlier forms of what was considered "AI" by companies were often very similar to advanced automation. These systems were based on predetermined rules and were mainly applied to repetitive, structured tasks such as invoice processing, inventory monitoring or compliance checks (Lichtenthaler, 2020). So they were useful in that sense, but their role was pretty limited. They improved speed and consistency, but did not change decision making significantly.

With the arrival of machine learning, things started to change more visibly. Machine learning represented another working paradigm compared to rule-based systems, as it is more data-oriented than instruction-oriented. The systems were able to identify patterns, evolve over time and generate outputs that were not explicitly programmed to do so in the first place. This change is often portrayed as a watershed and to some extent it is. But it is probably more accurate to see it as a continuation and not a clean break. But what changed was the role AI started to play. AI tools like predictive models improved for example, how companies forecast demand in areas like supply chains, and how to detect anomaly in suspicious transactions in finance. Functions on the customer side also changed, especially in the case of recommendation systems, which influence purchasing behavior (Raisch & Krakowski 2021). Artificial intelligence was no longer just a support function, it began to have an impact on decisions, even if not always in a visible way.

At the same time, another development made AI more pervasive, especially in larger organizations. Companies were turning more to software that already had AI capabilities built into it, rather than building AI systems from scratch. Tools such as ERP and CRM systems started to provide built-in analytics or predictive capabilities (Verhoef et al., 2021). In practice, this made adoption easier, as firms did not need highly specialized expertise to start using AI. What's interesting here is that AI frequently became part of the everyday work without being explicitly recognized as such. Employees may regularly use these tools, but they may not necessarily think of them as "AI," suggesting that adoption was, in some cases, more implicit than deliberate.

More recently, the emergence of generative AI has added yet another layer to this evolution. Such systems can generate text, code and other types of content, expanding AI into areas once thought to be less automatable. Now, AI tools can take over some tasks, such as writing reports, summarizing information or even helping with analysis. This raises rather different questions from those in the earlier stages. It is not just about increasing efficiency, but also how certain types of work can change over time (Kshetri et al., 2023). In some fields, like consulting or finance, AI is increasingly being presented as a kind of support for knowledge work. It is not clear, however, how far this will go and there is a tendency in literature to overstate its immediate impact.

This development is often explained by AI maturity models which try to illustrate the progression of organizations' use of AI. These models generally describe a transition from small-scale or isolated use to more integrated and organization-wide adoption (Jöhnk et al., 2021). That helps conceptually but can be a bit misleading as well. In practice, companies do not always progress smoothly or linearly. Some may develop rapidly in some areas and be very limited in others. So the notion of "maturity" should probably be considered a bit more fluid than these models imply.

Another important point is that technology capability alone does not ensure successful adoption. In practice, however, employee skills, data quality, and organizational support appear to be of primary importance. Some studies suggest companies that invest in these areas are more likely to benefit from AI than companies that focus more on the technology itself (Alsheiabni et al., 2018). This exposes a flaw in how we sometimes talk about AI as if you can simply implement it and it will automatically give us results.

On a broader level, we can see that AI in business has certainly grown over time. It started as a tool for automating routine tasks, progressed to decision support and is now increasingly involved in areas related to knowledge and creativity. That said, this progression is not to be considered fully complete or consistent across organizations. In many instances the various stages still co-exist. And so, although AI is often called transformative, the real world impact appears to be quite uneven depending on how and where it is applied.

2.2 AI Integration in Multinational Corporations

Introducing AI in multinational corporations (MNCs) is often more complex than smaller companies. This is mostly a scale issue. Large organizations have to work within different regulatory environments, and they operate in multiple countries. They often rely on legacy systems that are not always easy to update. Thus the deployment of AI is rarely a purely technical challenge. It often involves bigger questions about coordination, control and how different parts of the organization fit together.

One of the principal difficulties here is that of scalability. Companies often hope that in theory an AI solution built in one market can be used in another. In practice this does not always work as intended. Differences in data structures, legal requirements, language and local business practices can undermine the transfer of systems from region to region without significant adjustments (Bughin et al., 2018). What appears to be a scalable solution in the beginning is often highly context-dependent. Many companies are moving towards more flexible or modular systems where a basic model is kept but altered locally.

This links strongly to another issue: should AI be managed centrally or decentrally? Some MNCs choose to take a centralized approach, where a global team develops AI tools and then rolls them out across multiple units. This can enhance consistency and lower costs, and facilitate data governance (Mikalef & Gupta, 2021). At the same time it can also be limiting, particularly when local teams require faster or more customized solutions.

A decentralized approach, on the other hand, gives local units more control of the tools that they can experiment with that may better fit their specific needs. This can lead to innovation but can also lead to duplication and uneven development across the organization. In fact, many companies seem to take a combination of both approaches. The central systems are structured around shared data, and local teams adapt the applications according to their needs (Keding, 2021). It’s not always easy to find that kind of balance, but it seems to be more prevalent.

The usage of AI also differs quite a lot by industry. In some domains, like manufacturing or logistics, the focus is often on improving efficiency through forecasting or optimization. AI is more associated with risk analysis and fraud detection in financial services. At the same time, AI is more likely to be used to support research, analysis, or documentation rather than routine transactions in industries with a higher knowledge component, such as consulting or pharmaceuticals (Berente et al., 2021). This suggests that even within the context of multinationals, there is no one-size-fits-all model for AI adoption.

This is a good example of the pharmaceutical sector which works under strict regulatory conditions. In this industry, organizations must ensure that AI systems are effective, but also transparent and compliant with data, reporting, and validation rules (Topol, 2019). This can lead to slower but often more structured AI adoption. Many companies start by applying AI in support functions such as document processing or reporting before moving to more complex areas.

Trust is particularly important in these kinds of places. Employees are not just concerned about whether AI works, but whether its outputs can be justified, especially before regulators. This is why many organizations still use some type of human oversight when using AI systems. AI is often used in conjunction with human decision-making, rather than replacing it, as part of a more controlled process (Wirtz et al., 2020).

Summarizing, the adoption of AI in multinational corporations is driven by a combination of technological, organizational and contextual factors. The potential benefits are clear, but the actual process of adoption is often uneven and difficult to manage at times. So this is not a simple implementation, but rather a continuous adjustment. However, this research focuses more on strategic and structural aspects of AI adoption, and does not give much attention to how the employees experiencing this kind of implementations and changes across different regions and organizational contexts.

2.3 AI & Operational Efficiency

2.3.1 **Process Automation & Productivity**

Organizations frequently view process automation as one of the early areas where AI starts to have an effect. That said, automation in itself has been around for a long time so the difference is not always as clear as it sounds. What AI appears to bring is a bit more flexibility. These systems are able to not only follow hard rules but also handle tasks that are not entirely identical every time, as is often the case in administrative or compliance work (Bessen, 2018).

A typical example is robotic process automation for activities like invoices, reports or tracking internal processes. Simply put, it minimizes the manual work involved. This can save time and also helps to avoid errors, although the improvement is not always very visible at first. In many cases, it is a rather slow effect, with small changes across different tasks gradually accumulating over time (Syed et al., 2020). It's more about a series of smaller adjustments, not a big breakthrough.

Another point is how data is handled by AI. It should make life easier, in theory. Employees won't have to go hunting through different systems or repair inconsistencies. In practice it depends a lot on the already existing organization of the data. Some studies suggest that time is saved, but it is not always clear what happens to that time afterwards (Brynjolfsson et al., 2025). It doesn't necessarily mean better results automatically.

Not every firm benefits equally either. Organizations that are more organized seem to have their processes produce results faster, but some will have problems at the start especially if their workflows are not well defined (Davenport & Mittal, 2023). So it's not just the technology that explains the outcome.

Overall, AI-based automation does increase efficiency, but perhaps not as much as is often claimed. It changes how work gets done, but usually slowly and not always uniformly across the organization.

2.3.2 Decision Support Systems

The application of decision support systems in organizations has been gradually shifted towards AI integration. Historically, these systems were designed mainly for reporting past performance providing managers with insights of what had already happened. But now systems are also being used to look ahead, to provide predictions, or even to propose possible actions. As a result, decision-making becomes not only faster but also different in style as managers begin to, at least to some extent, base their decisions on algorithm-based recommendations (Shrestha et al., 2019).

This becomes quite visible in one area, forecasting and risk assessment. Machine learning models can leverage large amounts of data from different sources and generate predictions that would be difficult to generate manually. For instance, in supply chains, they can warn you of potential disruptions or shifts in demand before they actually become problems. In more regulated environments similar systems are employed to detect anomalies or compliance issues in an earlier stage (Makridakis et al., 2020). This does push decision making a little away from reacting to problems and more into anticipating them.

Another benefit of these tools is that they democratize data across the organization. Dashboards and AI-powered tools allow more employees to interact with data directly, so insights are not limited to specialized analysts anymore. This can speed things up and make organizations more responsive. At the same time, it also raises the question of over-reliance on such systems, particularly when the underlying logic is not always transparent (Jarrahi, 2018). So decision making gets a little more mixed between human judgment and system generated input.

But it doesn't always work the way it should. They tend to be useful if they integrate well into existing workflows. They cannot be used if they are too complicated or hard to understand, even if they are technically advanced. Employees tend to accept them more intuitively if they are easy to understand and fit with the way decisions are already made (Kunc & O’Brien, 2019). This implies that the success of decision support systems is not only about their capabilities but also about their adoption and use in practice.

So AI has certainly expanded what decision support systems can do, but their real-world effects seem to differ. Sometimes they improve both the speed and quality of decisions, but sometimes they add complexity or create new kinds of dependency.

2.3.3 **Cost Reduction & Performance Metrics**

AI is often spoken about in terms of cost reduction, productivity and decision making. Many companies seem to approach it with the expectation that it will lower costs in a fairly direct way, for example by reducing manual work or by avoiding errors. But this doesn't always happen right away. Often, the financial effects are slower and less obvious than anticipated (Huang & Rust, 2021).

AI can reduce costs by eliminating mistakes and making processes more stable. For example, anomaly detection or process monitoring systems can help avoid problems in supply chains or compliance related activities. This may cut down on things such as rework, delays, or even penalties, though such savings are not always easy to be directly measured (Chui et al., 2018). So there is an effect, but sometimes it is indirect, or spread out over time.

There is also a change in how performance is monitored. AI tools allow companies to see what's happening in real time, not just in reports. This seems like a clear improvement, but it also alters what is being measured. In addition to the output there is more focus on things like accuracy or responsiveness (Wamba-Taguimdje et al., 2020). These newer metrics are in turn not always simple and can be a little difficult to interpret in some cases.

Another problem is that AI is not a free tool to use. That usually means investment, not just in technology, but in training and data management. Some organizations seem to benefit more when they integrate AI with wider changes to their processes, rather than just plugging the technology in (Fountaine et al., 2019). This means the results are not only related to the system itself.

All in all, AI does seem to help efficiency, but not necessarily in the straightforward way it is often presented. Instead of direct cost reductions, it often results in changes in how performance is perceived and tracked over time. It should be mentioned that many of these studies give light only to the measurable performance outcomes and most of the times exclude how employees experience such improvements in their daily work.

2.4 Workforce Transformation & Organizational Change

2.4.1 **Job Redesign and Task Automation**

Usually, when AI use is included to everyday work, it doesn't mean whole jobs go away. What seems to happen more often is that certain tasks within those jobs change instead. Recent studies increasingly highlight that jobs are not single fixed units, but a combination of different activities. AI will take over the more repetitive or data-heavy parts, but the other parts of the job will be still there. Therefore, roles are often altered rather than abolished, with workers shouldering increased responsibility for checking, interpreting or coordinating the outputs generated by these systems (Autor & Reynolds, 2020).

This becomes very clear in areas where work is already digital, such as administration or compliance. Checking documents, reconciling data or producing standard reports are tasks now that can be automated, to some extent. As these tasks are reduced, the overall structure of the job is changed. Theoretically, this frees up time for higher level or more complex activities such as communicating across teams or dealing with exceptions. However, in practice, this shift is not always clear-cut or immediate, as automation is generally introduced gradually rather than all at once (Acemoglu & Restrepo, 2020).

At the same time, the replacement of routine tasks does not necessarily make work easier. Sometimes it's the other way around. The other tasks can be more demanding, because employees have to interpret the system outputs or intervene when something is not going as expected. This can raise the level of responsibility and in some cases even blur the lines between roles. Routine work may decrease, but the overall complexity of the job may even increase (Narayanan et al., 2021).

Organizations don't always respond the same way to this. Some seek to formalize roles, to create roles that combine operational knowledge with oversight of AI systems. Others automate without clearly updating job descriptions, and this may contribute to some confusion about who is responsible for what. Some evidence suggests that when companies follow a more systematic approach, by explicitly redefining tasks and roles, employees are more likely to adapt and accept AI (Tambe et al., 2019).

In general, job redesign appears to be less a matter of the technology itself and more a matter of how organizations choose to implement it. Although AI is expected to eliminate some tasks, it is not known how the tasks will be reallocated. It's a function of choices made by management and the larger environment the company operates in. So, AI not only changes the work that gets done, but also the way that work is structured and conceptualized within the organization.

2.4.2 **AI as Augmentation vs Replacement**

One of the most common debates in the literature on AI and employment is how to interpret AI, whether it is mainly replacing human labor or is better understood as something that supports and extends human work. Initially the replacement argument is the most salient, especially in public discourse where AI is framed as a direct threat to jobs. But if we look at the organizational settings more closely, the picture looks less clear. AI does not completely eliminate the need for human involvement in many cases, but it changes the way work is divided between people and systems (Brynjolfsson, Rock, & Syverson, 2019).

The replacement view is linked with tasks that are repetitive, predictable and easy to standardize. This includes areas such as data handling, document checking and some areas of customer service. In these cases, it is obvious that AI will be able to take over work done by employees, and this is why concerns about job displacement keep appearing in academic and professional discussions (Susskind & Susskind, 2022). But I think it would be too simple to call this a straightforward replacement. Even in areas of high automation, there's usually a need for someone to oversee the system, check the outputs, or intervene when something goes wrong. The so called "replacement" side often still uses human judgement in practice.

In many organizational contexts the augmentation perspective appears more convincing. Here, AI is not seen as a replacement for employees but as a tool to enhance their work. It can help people process information faster, compare alternatives or handle more complex analytical tasks. So AI might help us do better than we could by ourselves, rather than taking our place. To some extent, research supports this view, suggesting productivity and acceptance are often higher when AI is implemented as a complement to human expertise and not an alternative (Dell'Acqua et al., 2023). So it's not just about what technology can do, but also how it is placed in the workplace.

This debate is more complicated because in reality organizations often undergo both processes at the same time. Some of the roles are automated, while other aspects require more effort, such as when employees are asked to work with AI outputs, interpret recommendations, or manage exceptions. This creates a kind of hybrid situation where jobs are neither simply replaced nor supplemented, but slowly reconfigured. So the line between augmentation and replacement can sometimes appear overly simplistic compared to what is really happening inside firms. As Kellogg, Valentine, and Christin (2020) suggest, the relationship between workers and AI is often not one that is settled from the outset, but rather one that is reconfigured over time.

Another thing that one should not forget is the role of management. How AI is introduced makes a significant difference in how employees perceive it. In organizations where AI is positioned as a cost-saving tool first and foremost, workers are more likely to associate it with replacement, even if the automation is only partial. On the other hand, when companies invest in training and make AI part of the way employees can help them do their jobs, the response is less defensive and more welcoming. This means that the reactions of employees are not only determined by the technology but also by the story about the technology.

On the whole, I'd say that AI is rarely one thing or the other. It can substitute for some jobs, but also augment others, sometimes in the same job. That is why it may be more useful to think of AI not in binary terms but as part of an ongoing process of workplace reconfiguration, where the balance between human and technological input is constantly being adjusted.

2.4.3 **Skills Shift and Digital Upskilling**

As AI becomes more integrated into everyday work, it seems that the effects are more likely to be felt through changes in skill requirements rather than job displacement. In many cases, AI takes over some of the more routine parts of a job, but that does not mean the job gets easier. If anything, it often shifts the focus to skills such as digital literacy, analytical thinking and the ability to work across teams. Employees should not only use AI tools, but also understand what they are doing, question the results when necessary, and apply them in a sensible way in the context of broader work processes (Frank et al., 2019). This implies that the nature of professional competence is changing gradually.

One of the striking things in literature is the growing importance of hybrid skills. Increasingly, employees in finance, compliance, marketing and supply chain management need to work with dashboards, automated systems and different types of digital data. This is not to say that everyone suddenly needs to be a technical expert, but it does mean that a basic understanding of data, systems and digital workflows is becoming increasingly difficult to avoid (Lund et al., 2021). This is one of the more impactful changes AI will bring for me, because it won't only affect specialized roles, but also jobs that were not considered "technical" roles.

This has led many organizations to start focusing more on upskilling. Training initiatives in AI and digital tools have become more common, particularly in multinationals. These often include data literacy sessions, awareness workshops or more targeted training linked to specific roles. Such efforts can boost employee confidence and mitigate resistance to adoption of AI, as literature suggests (World Economic Forum, 2020). However, training should not be seen as an automatic solution at the same time. Sometimes organizations implement these programs because they seem needed, but this does not always mean that they are well designed or really useful in practice.

This is probably where the issue gets a bit more hands on. Training is more effective if it is closely connected with the real tasks of the employees, rather than being very general. If people attend broad awareness sessions but return to jobs where they are not sure how to apply what they learned, the impact is likely to be limited. More contextualized approaches in which learning is coupled to specific systems and workflows seem to be more effective (Muro, Maxim & Whiton, 2019). So, upskilling is not just about training people, but about making sure it is actually relevant to the work people are doing.

In general, the change in skills involved with AI is more than learning to use new tools. It's also about being flexible, being a lifelong learner, and being comfortable working with intelligent systems. These qualities seem to matter more and more in digitally changing organizations. Yet it is also clear that not all employees or firms are equally prepared for that shift. While these studies provide important key insights regarding how jobs are transforming, they sometimes ignore how the employees interpret and respond to such changes.

2.5 Employee Perceptions of AI

2.5.1 Technology Acceptance Models

Many studies about how employees react to AI rely on already existing models to explain acceptance and behavior. These frameworks attempt to explain the reasons why people decide to use or resist new systems and they tend to show that it is not just about how good technology is. Perceptions, expectations and the wider organizational environment are also important.

One of the most commonly used models is the Technology Acceptance Model (TAM) introduced by Davis (1989). It focuses on two key ideas: perceived usefulness and perceived ease of use. In short, if employees believe a system makes them better at what they do and is not too difficult to use, they are more likely to embrace it. The model was developed long before these technologies became common, but it still seems quite relevant for AI (Venkatesh & Bala, 2008). At the same time, I think TAM can be a bit constraining when applied to AI, primarily because it doesn't fully account for some of the uncertainty that comes with these systems.

More developed models like UTAUT come in handy here. The Unified Theory of Acceptance and Use of Technology adds other factors such as social influence and organizational support. What this means is that employees don't decide for themselves about tech. They are influenced by colleagues' opinions, managers' expectations and provision of organizational support to actually use these tools (Venkatesh et al., 2012). In environments where AI is still a bit of a novelty, this kind of influence can be quite powerful, as humans tend to look to others before developing their own opinion.

There's also a growing feeling that the traditional models don't fully account for how people react to AI. AI can be less transparent, more difficult to understand and sometimes unpredictable compared to older systems. Then things like trust or perceived fairness start to enter the picture. Employees may wonder not only whether it is useful, but also whether they can trust it, and whether it makes fair decisions (Glikson & Woolley, 2020). Older models tend to have a harder time capturing these sorts of questions, which is probably why more recent studies try to expand them.

So, while models such as TAM and UTAUT still serve as a useful starting point, they may not be sufficient on their own. They tell part of the story, but AI adds additional layers of complexity that go beyond the ease of use or usefulness. In practice, employee acceptance appears to be a function of technical performance, organizational context and comfort with dependence on such systems in daily work.

2.5.2 **Trust, Fear, Resistance, and Adoption Factors**

Technology acceptance models are useful, but they cannot explain employees' reactions to AI in real organizational settings. Equally important, it seems, are the more human elements like trust, uncertainty and fear of losing control over your work. Often, people have an opinion about AI before they've used it much, because the very idea of automation carries with it certain assumptions and concerns.

One of the most important factors influencing whether employees will use AI or not seems to be trust. If the system looks reliable and the outputs are reasonable, then people are generally more open to it. But what if the results seem inconsistent, unclear, or difficult to explain? Trust erodes pretty quickly. What the literature shows is that technical accuracy alone is not enough. Employees also appear to care about whether the system is understandable and whether there is still some room for human judgement or intervention (Glikson & Woolley, 2020; Shin, 2021). This is especially relevant in AI, where many systems are not very transparent, even when they perform well.

A lot of the resistance isn't about what AI is doing now, but what employees think it might lead to in the future. Concerns about job loss, loss of autonomy or increased monitoring can have a strong influence on attitudes, even when the technology is introduced as a support tool rather than a replacement (Brougham & Haar, 2018). This tells that the employee answers are often driven by uncertainty and not by real experience. If people don't understand what management is trying to do, they're more likely to see AI as a threat.

But resistance isn't always obvious. That does not necessarily mean that employees openly reject the system. More often it appears in more subtle ways. People may not pay attention to some of the features, stay in their old habits, or be cautious about the outputs produced by AI. I don't think this should be interpreted as unwillingness to change. Sometimes it may simply be a question of protecting professional judgement or a modicum of control over the work process.

Another point worth noting is that the way in which AI is introduced is a major determinant of adoption. Resistance is probably more likely to occur when communication is vague or when employees feel decisions are being forced upon them. Conversely, attitudes are more positive when organizations provide clear reasons for the use of AI, involve employees in the process, and provide appropriate training (Jia & Zhou, 2024). So the problem is not just the technology, but the way it is framed within the organization.

In that regard, trust, fear and resistance are not marginal issues. They're part of the adoption process itself. AI might have the technical edge, but whether employees actually embrace it seems as much about how safe, informed and involved they feel in its rollout.

2.5.3 Organizational Culture and Leadership Influence

Besides the technology itself and the individual attitudes of the employees, the broader organizational context appears to be an important factor in how workers react to AI. Culture, for example, can influence whether AI is viewed as a good or bad thing. In organizations that promote experimentation and learning, employees might be more willing to try new tools even if they don't fully understand them to begin with. On the other hand, the same technology may be more suspect in more rigid environments. In this sense, culture does not directly determine adoption but does seem to influence the level of comfort people have with change (Nambisan et al., 2019).

Leadership is important too, very much so. Usually it's managers who explain why AI is being introduced and what it's supposed to do. This means that the way they communicate can influence how employees perceive these changes. When leaders are open about the purpose of AI and show some faith in its value, employees are generally more open to engaging with it. On the other hand, when there is little or unclear communication it can cause uncertainty, and even mistrust. According to the literature, it is not only about deploying the technology but also managing it on a day to day basis (Raisch & Krakowski, 2021).

Another important factor appears to be the employees' perception of support during transition. Organizations are likely to achieve more positive employee reactions by providing training and involving employees in the process. People will engage with AI more if they feel like they're being properly prepared for it, rather than just expected to adapt on their own. At the same time, it is important to note that not all training is equally effective, especially when it is too generic or disconnected from real tasks. However, the intention to support employees seems to play an important role (Strohmeier & Piazza, 2019).

All these points collectively show how organizational culture and leadership serve as a filter through which AI is interpreted. The same technology can also be received very differently, depending on how it is introduced, explained and supported. Therefore, adoption is not only about the system itself but also about the environment in which the employees are supposed to use it. However, it is important to note that such perspectives may oversimplify employee responses and may not completely capture the complexity of attitudes and perceptions toward AI in everyday work environments.

2.6 Ethical and Governance Issues in AI Adoption

2.6.1 **Bias and Fairness**

Issues of bias and fairness are moving from the theoretical discussions to everyday business concerns as AI systems become more deeply embedded in organizational processes. In simple words, AI is not independent of the data on which it is trained. If those data reflect existing inequalities, which they often do, then the system may reproduce or even reinforce these inequalities. This is not necessarily intentional, but it does cast serious doubt on how well organizations truly understand the outcomes that these systems generate (Mehrabi et al., 2021).

This is especially the case in areas such as recruitment, performance evaluation or customer profiling. In such settings, even small biases can have observable effects, especially when decisions are made at scale. What makes it more difficult is that bias is not always obvious. It may be an indirect appearance, for example, through variables that appear neutral but still reflect underlying patterns in the data. This may lead organizations to be unaware that a system is producing unfair outputs (Barocas, Hardt, & Narayanan, 2023).

As a result, many companies have begun to incorporate measures such as fairness checks or algorithmic audits during system development. They are intended to find potential problems and fix them before systems are rolled out widely. However, it is not perfectly clear how effective these technical solutions are by themselves. As indicated by literature, bias can never be completely eliminated just by better models or data. There also needs to be some level of oversight too, with different perspectives and ideally with clear accountability structures (Leslie, 2019).

Therefore fairness seems to be not only a technical challenge. It is also linked to how organizations choose to govern and manage AI more broadly. Fair outcomes require continued attention, not just at the design stage, but during implementation and use. In that sense responsibility is not only with the system, but with the whole organization.

2.6.2 Transparency and Accountability

In conversations about AI in organizations, fairness now has a new companion topic: transparency. One common problem is that many AI systems, especially the more advanced ones, are not easy to understand. Even the people who make them may not fully explain how a particular output was produced. This becomes a little problematic when these systems begin to influence decisions, particularly in cases where accountability is crucial, such as performance appraisal or operational decision-making (Burrell, 2016).

That said, transparency doesn't mean all the technical details have to be explained in full. More often it seems a matter of whether decisions can be understood well enough to justify them. For example, in more regulated industries, companies may need to show what data was used, how a recommendation was generated, or what role human oversight played in the process. Without such clarity, it is unclear who is responsible for the outcome , the system itself, the developers or the managers who use it (Mittelstadt et al., 2016). That can make accountability difficult in practice.

In response, some organizations attempt to create more regimented processes, such as maintaining precise records of how systems function, or inserting human checks into decision processes. This is to make AI-backed decisions more traceable and contestable, if necessary. It also appears that employees are more willing to trust these systems when they feel they can understand them at some level, or when they know there is a way to challenge a result (Kroll, 2015). So transparency is not only about following the rules, but also about whether people feel comfortable with using these tools.

At the same time, demanding full transparency is probably unrealistic, especially with more complex AI models. Sometimes, there's a trade-off between system performance and explainability that organizations have to deal with. This means that transparency is less of a fixed requirement and more of a balancing act depending on the situation.

2.6.3 **Data Privacy and Regulatory Context**

Another area that becomes difficult once AI is introduced is data privacy, especially for multinationals. Most AI systems are built with huge datasets, and these data sets often contain very sensitive information, whether it's about employees, customers or internal operations. As a result, it's hard to look past questions about how data is handled. Regulations like the GDPR are strict, notably with regard to consent and automated decision-making (Voigt & von dem Bussche, 2017). But even with these frameworks, applying them in practice is not always straightforward.

The situation gets even more complicated when companies operate in different countries. Data protection laws vary from country to country and often restrict the transfer or storage of data across borders. This means that decisions about where data is stored or how AI systems are trained are not purely technical decisions (Cath et al., 2018). Some firms have compliance teams or internal structures to deal with compliance, but this can be an extra layer of complexity and slow things down.

But, at the same time, privacy is not only a legal issue. It also affects employees' feelings about AI in their daily work. Monitoring or analyzing systems can easily be perceived as invasive, particularly when people are unsure of how the data is used. Even if the intention is not bad, the lack of clarity can still be uncomfortable. Some studies suggest clear communication as a help, but this does not always happen in practice consistently (Floridi et al., 2018).

So privacy, in a way, becomes more than a regulatory requirement. And it has to do with trust, too. When the handling of data is perceived as responsible, employees are more willing to accept such systems. If not, even useful tools may meet resistance. Thus, privacy is a continuous problem rather than an entirely solvable issue at the implementation stage.

2.7 Literature Gap and Conceptual Framework

While research on AI in organizations has increased rather rapidly in recent years, there are still a few noticeable gaps, especially considering multinational companies. There are many existing studies that tend to focus on one side of the story. Some concentrate mainly on performance results, like efficiency or productivity, and others are more about labor-related issues, like automation and job risk. Research that combines these aspects, and that studies them within the same organizational setting, is less common (Raisch & Krakowski, 2021). Thus, the real interplay between technical improvements and employee experiences is not always straightforward.

Another issue is the type of data used in many studies. Many of them are either single-industry samples, controlled experiments or large macro-level analysis. These approaches are useful, but they don't always represent what happens inside big organizations day-to-day. This is especially interesting for multinational corporations, which combine different departments, regulatory environments, and types of work within one structure. AI adoption in these contexts is rarely isolated. It often involves several layers at once, such as operational processes, governance, and employee adaptation (Jöhnk et al., 2021). This provides a useful, but still underexplored, context.

This study takes a slightly different approach to attempt to fill these gaps. Instead of only looking at technical performance, it looks at the real experience of AI for employees in their day to day work. It's about linking what's going on at the operational level, like efficiency or decision-making, to the way employees see and respond to those changes. This allows for a more integrated view rather than looking at these dimensions in isolation.

The logic of the conceptual framework of this study is similar to this. It combines variables that have been used in previous studies, especially in areas such as technology acceptance and organizational change, but in a more integrated way. The most relevant independent factors are provided by the use of AI in work processes and the degree of automation of tasks. The results are classified into two classes. One is focused on operational issues like perceived productivity, decision support and process reliability. The other is around workforce-related issues, including how employees feel about switching jobs, upskilling, and their general attitude toward AI.

Moreover, the model incorporates perception-based factors, such as usefulness, ease of use, trust, and organizational support, which are well-known constructs in the existing literature (Venkatesh et al., 2012, Glikson & Woolley, 2020). This is important because they can be relatively easily measured using survey data and have been tested in similar contexts.

This highlights the need for studies that combine both organizational and employee-level perspectives in order to provide a more comprehensive understanding of how AI adoption is experienced in practice.

This structuring of the study aims to get a little closer to what actually happens in organizations, rather than remaining at a purely theoretical level. It helps to bridge the gap between the more general conversation around AI transformation and what employees experience in practice when they use these systems every day. The framework also guides the development of the methodology and the design of the questionnaire in the next chapter.

3 RESEARCH METHODOLOGY

3.1 Research Philosophy & Approach

This study adopts a positivist research philosophy, assuming that phenomena within organizations can be observed and measured relatively objectively. This method is normally used in the studies which aim to find the relationships between variables and test the hypotheses with data. In this way concepts such as the use of AI, operational efficiency, and employee perceptions are turned into measurable variables, which in turn enables them to be analyzed in a more structured and systematic way.

The study is based mainly on a quantitative approach. The aim is to identify patterns and relationships between AI integration and both organizational outcomes and employee-related factors. Structured questionnaire was used for data collection from employees working in multinational or AI-enabled environment. This makes it easier to compare responses and apply statistical methods in order to identify trends or correlations.

At the same time, the study does not limit itself to a purely quantitative approach. Some of the included variables, such as trust, resistance or perceived usefulness are more subjective in nature. They are measured through Likert scale questions, but they still reflect personal experiences and interpretations. Even if data is gathered in a structured way, there is still a small interpretative element to the understanding of the results.

The synergy of these elements enables the study to strike a balance between structure and some degree of flexibility. On the one hand there is the quantitative approach with clarity of measurement and comparability. In contrast, the inclusion of perception-based variables helps to capture how employees actually experience AI in their daily work. This combination is more appropriate, as AI adoption is not just a technical issue, but something that affects people, and organizational dynamics more broadly.

3.2 Research Design

The study's research design is based on the cross-sectional survey model. This basically means that data was collected from the participants at one point in time rather than over a long period of time. This choice is suitable for the purpose of the study which is to understand the way employees perceive AI and how it is used in their organizations. In this sense, the study aims to capture a snapshot of the situation, rather than examine changes in time.

Data was gathered through a structured questionnaire. The questionnaire was sent to employees who work in organizations where AI is implemented in some form. The majority of the questions were closed-ended and based on Likert scales as this facilitates comparison and analysis of the responses. This format is also suitable for the statistical analysis required to test the research hypotheses, although it may limit the detail to which participants can respond.

The research is not limited to a single organization but involves participants from various companies. The sample does not focus only on a specific sector, as it seemed important to have participants from different organizations, sometimes, different industries, to get a broader set of experiences. This approach may also introduce some variation in responses at the same time as working environments and AI usage can vary quite a bit across firms.

The cross-sectional survey design provides a feasible way of collecting data relevant to the research aims. This enables the research to investigate relationships between variables in a wider sample of participants but at the same does not show how these relationships may change over time.

3.3 Population & Sampling Strategy

The research is done among employees working in organizations where AI is already used in one way or another. These are typically companies that are more digital, so AI is touching things like operations, customer service or data analysis. The focus is on larger or multinational firms, mainly because the use of AI tends to be more structured in these firms.

As it is not really possible to access a clearly defined population, a non-probability sampling approach was used. In practice this meant that convenience sampling was predominantly used. Participants were approached through existing contacts (e.g. colleagues or professional contacts). This made it easier to collect the answers, especially under the time constraints and difficulty of direct access to organizations.

Simultaneously, snowball sampling was also used to expand the sample. A total of 216 valid responses were collected and processed during the final analysis. Those who filled out the questionnaire were asked to pass it on to others they know who work with AI. This increased the number of responses, but also means the sample is heavily dependent on personal networks. This means that some types of participants may be over-represented compared to others.

Of course, this type of sampling has its limitations. The sample is not fully random and does not permit complete generalization to a broader population. However, this was considered acceptable for this type of study, as the aim is more exploratory and focuses on identifying patterns rather than producing precise population estimates.

There was some effort to get people from different roles and departments, just to avoid a very narrow perspective. Responses may still vary depending on the type of organization or how much they're using AI.

3.4 Questionnaire Design

The questionnaire used in this study was not developed from scratch. Most of it is taken from ideas and concepts that are already in literature like use of AI, efficiency and how employees perceive it. The main purpose was to take those concepts that already existed and adapt them to the context of the present research.

The questionnaire was developed based on an extensive review of the literature around AI adoption, technology acceptance, trust in AI, operational efficiency, workforce impact, and organizational support. In cases where it was possible, measurement items were adapted from previously validated scales rather than being created completely by the researcher. The wording of the items was slightly adjusted so that it would fit the context of AI use in modern corporations while keeping their original meaning.

The questionnaire consists of eight constructs: AI Usage, Perceived Usefulness, Perceived Ease of Use, Operational Efficiency, Workforce Impact, Trust in AI, Fear and Resistance, and Organizational Support. Each construct was measured using multiple items to improve reliability and adequately capture the underlying concept.

It was broken down into a few parts just so it was easier to follow. It starts with some general questions (age, role, experience etc.) These are mostly meant to provide some background information about the participants. These are not directly related to the hypotheses but will be useful later when we look at the data.

After that, the questionnaire moves more towards AI itself. One question is how AI is actually used in the workplace. This felt necessary as talking about AI in general is a whole different deal than understanding whether people actually use it in their daily tasks. Some of these questions were loosely based on previous studies (Venkatesh et al., 2012; Mikalef & Gupta, 2021), but they were simplified a bit.

Then, there is a section on utility and ease of use. This comes from TAM (Davis, 1989) which is still very popular in this type of research. It is a little bit old but still it is a very basic way of understanding how people perceive new systems (Venkatesh & Bala, 2008). The questions here are pretty basic, highlighting whether AI is helpful and if it is easy to use.

Another section concerns efficiency. Work faster, make fewer mistakes, make better decisions. These are of course only perceptions, and therefore not entirely objective, but they do provide an indication of the experience of AI.

There are also some questions on job changes. The question is less, ‘Is AI replacing jobs?’ and more, ‘Are tasks changing or becoming automated?’ This seemed more plausible, since in practice jobs are not usually just ‘removed’ altogether (Acemoglu & Restrepo, 2020; Brynjolfsson et al., 2019).

Trust is also included, as it appears quite often in the literature. The questions here are about whether employees are comfortable to trust AI or not (Glikson & Woolley, 2020; Shin, 2021). There are also some questions about concerns, such as job security or preference for human decisions (Brougham & Haar, 2018; Laumer et al., 2019). They are quite close, so they were grouped in a similar way.

And then there are some things about organizational support. This includes training or encouragement to use AI. These factors are mentioned in studies like UTAUT (Venkatesh et al., 2012) so it seemed reasonable to include them.

All questions are rated on a five-point Likert scale (strongly disagree to strongly agree). This is pretty standard and makes the data easier to analyze, even if it makes some answers easier.

The items of the questionnaire were adopted from established constructs in the literature, especially the Technology Acceptance Model (TAM) and similar frameworks (e.g., UTAUT).

The perceived usefulness and ease of use items were adopted from Davis (1989) and Venkatesh et al. (2012) whereas other constructs such as trust, organizational support and workforce impact were informed by more recent studies on AI adoption.

Although the questionnaire was not directly adopted from a single validated instrument, content validity was ensured by aligning items with widely accepted theoretical construct. Some of the questions were slightly amended so that they can better fit to the general context of AI in corporations. Before proceeding to send out the questionnaire to the employees, it was carefully reviewed to ensure that the questions were clearly reflected and easy to understand.

3.5 Data Collection Process

For this study, data was collected through an online questionnaire that was distributed to employees working in organizations where AI is used. Using an online survey made things easier in terms of distribution as people could fill it out when it was convenient for them. It was also helpful to reach people working in different companies, without the need to have direct access.

The questionnaire was also distributed following the same sampling approach as mentioned above. At first it was mostly shared with people I had easier access to, for example colleagues or professional contacts, especially those in multinational or AI-related environments. Most of them were from the finance and telecommunication sector in Greece, but not all answers came from just that area. Then the participants were asked to send the questionnaire to others that they know, which increased the number of answers. This worked quite well in practice, even if it means that the sample is somehow dependent on personal networks.

Participants were provided with a brief introduction prior to completing the questionnaire explaining the purpose of the study. It also said participation was voluntary and the answers would be kept confidential. This was important, not least because some of the questions touch on topics such as job security or perceptions about AI that people may not otherwise feel comfortable answering.

The questionnaire was available for a defined period and responses were monitored during this period to check sample size was developing as expected. All responses were collected anonymously, and no personal identifiers were used. This was mainly to make the participants more comfortable to answer honestly.

After data collection, responses were transferred into a spreadsheet for analysis. In this phase the data had to be cleaned and structured, e.g. by checking for incomplete responses and grouping variables according to the questionnaire structure. It took time, but it had to be done before the statistical analysis could be started.

3.6 Data Analysis Methods

In this study a combination of descriptive and inferential statistical techniques was used to analyze the data. The first aim was to develop a general understanding of the sample, while the second was to look for relationships among the main variables in order to answer the research questions. The primary analytical tool was IBM SPSS Statistics. Microsoft Excel was also utilized in the initial phases for organizing and checking the dataset.

The specific statistical techniques were selected due to nature of the data and the objectives of the study.

Descriptive statistics were used to summarize the sample and provide a general overview of the responses. Demographic variables (age, gender, department, years of experience, and company type) were presented in frequencies and percentages. In addition, means and standard deviations were calculated for the main study variables, as well as skewness and kurtosis indicators, mainly to check for any strong irregularities in the distributions before proceeding further.

Before examining relationships between variables, the reliability of the measurement scales was tested using Cronbach's Alpha. Each construct of the questionnaire was evaluated individually. All values were above the generally accepted threshold of 0.70, suggesting that internal consistency was adequate. This step was necessary to make sure that the items within each construct were measuring the same underlying concept and could therefore be aggregated into composite variables.

Differences among demographic groups were analyzed using Kruskal–Wallis H test. The Kruskal–Wallis H test was chosen because several independent variables were categorical, while the dependent variables were based on Likert-scale responses. As Likert-scale data are ordinal and may not satisfy normality assumptions, a non-parametric test was considered more suitable than one-way ANOVA. It was applied to variables such as age, gender, department, years of experience, type of company, etc. The test helped to identify whether there were statistically significant differences in the perception or usage of AI in the workplace by different groups.

Relationships between the main variables were explored using Spearman's rank-order correlation. This method is chosen because it is suitable for ordinal data derived from Likert scales and does not require normally distributed data. This allowed the study to explore the association between variables such as AI utilization, perceived utility, confidence, operational effectiveness, and organizational backing. The results showed some strong positive correlations and fear and resistance were negatively correlated with most of the adoption-related variables.

Finally, multiple linear regression analysis was carried out to assess the extent to which selected independent variables predicted key study outcomes. Two separate models were developed: one targeting operational efficiency, the other workforce impact. Regression analysis assumes interval-level data but is frequently employed in similar research with Likert-scale constructs, particularly when scale reliability has been demonstrated. The step was to look at the combined effect of variables, and to find which factors had the strongest explanatory power when considered together.

These approaches enabled the analysis to go beyond basic description, and to identify meaningful patterns within the data. At the same time, it should be emphasized that the results indicate associations between variables and not causality, especially considering the cross-sectional and perceptual study nature.

3.7 Reliability, Validity & Ethics

Construct validity refers to whether the questionnaire accurately measures the theoretical concepts it intends to measure. In this study, this was supported by using questions from previous research and established theories.

Specifically, the constructs of Perceived Usefulness and Perceived Ease of Use were derived from the Technology Acceptance Model (Davis, 1989), while Organizational Support was informed by the UTAUT framework (Venkatesh et al., 2012). Trust in AI, Workforce Impact, and Fear and Resistance were adapted from previous studies examining employee perceptions of AI implementation.

Content validity was further empowered by reviewing the questionnaire questions against the research objectives and hypotheses to ensure that all important aspects of AI adoption and its impact on organizations were covered.

To assess the reliability of the scales employed in this study, Cronbach's Alpha was calculated for each construct. Items were classified according to the framework developed previously from literature. These were AI use, perceived usefulness, perceived ease of use, operational efficiency, impact on the workforce, trust in AI, fear and resistance and organizational support.

It was noticeable in this process that some of the questionnaire items were negatively phrased. For example, statements like "AI may reduce the need of certain roles in the future" (Q23), "I am concerned that AI could replace my job" (Q28), "AI makes me feel uncertain about my future role" (Q29), "I prefer to rely on human judgment over AI" (Q30), "I am hesitant to fully adopt AI tools" (Q31) do not reflect positive attitudes but rather concerns or hesitation towards AI.

However, these items do not represent the same underlying concept. The item "AI may reduce the need of certain roles in the future" (Q23) was retained within the Workforce Impact construct, as it reflects perceived changes in job structure.

In contrast, items such as "I am concerned that AI could replace my job" (Q28), "AI makes me feel uncertain about my future role" (Q29), "I prefer to rely on human judgment over AI" (Q30), and "I am hesitant to fully adopt AI tools" (Q31) were grouped under a separate construct labelled "Fear and Resistance", as they capture employees' attitudes and reactions toward AI rather than its direct impact on work.

This approach was considered more appropriate, as these questions are clearly measuring a different aspect than constructs like usefulness or trust. Resistance and trust are also often treated as separate dimensions in the literature, rather than being two ends of the same spectrum, so this seemed a reasonable approach. This was to ensure that all items within each construct were in the same direction and mean values were computed for each scale.

As seen in the results, all constructs had acceptable levels of internal consistency. The Cronbach's Alpha values ranged from 0.745 to 0.894, which are above the commonly used threshold of 0.70. The "Trust in AI" ($\alpha = 0.894$) had the highest value followed by "AI Usage" ($\alpha = 0.878$) and "Organizational Support" ($\alpha = 0.865$) and showed a good fit for these items.

Other constructs such as "Perceived Usefulness" ($\alpha = 0.842$) and "Ease of Use" ($\alpha = 0.834$) also demonstrated good reliability. The "Workforce Impact" ($\alpha = 0.776$) and "Fear and Resistance" ($\alpha = 0.745$) subscales were slightly lower but still acceptable. Not too surprising though, these areas are a little broader and may contain more diverse perceptions.

In general the results indicate an adequate reliability of the scales used in this study to proceed with further analysis. It is also important to note that some constructs are inherently more complex and this may explain why their reliability is slightly lower than other constructs.

Ethical principles were followed throughout the study, as participation was voluntary, respondents were informed about the purpose of the research, and consent was obtained before questionnaire completion. All responses were collected anonymously, and the data were used exclusively for academic purposes and stored securely in accordance with research ethics principles.

Table 1: Reliability Analysis of Constructs (Cronbach's Alpha)

Construct	Number of Items	Cronbach's Alpha
AI Usage	4	0.878
Perceived Usefulness	3	0.842
Ease of Use	3	0.834
Operational Efficiency	4	0.861
Workforce Impact	4	0.776
Trust in AI	4	0.894
Fear & Resistance	4	0.745
Organizational Support	4	0.865

4 FINDINGS

4.1 Descriptives

In terms of age, most participants are between 26 and 35 years old (44.44%). The next biggest group is those aged 36–45 (31.94%). Fewer respondents fall into the 18–25 category (16.67%), and only a small number are 46 or older (6.94%).

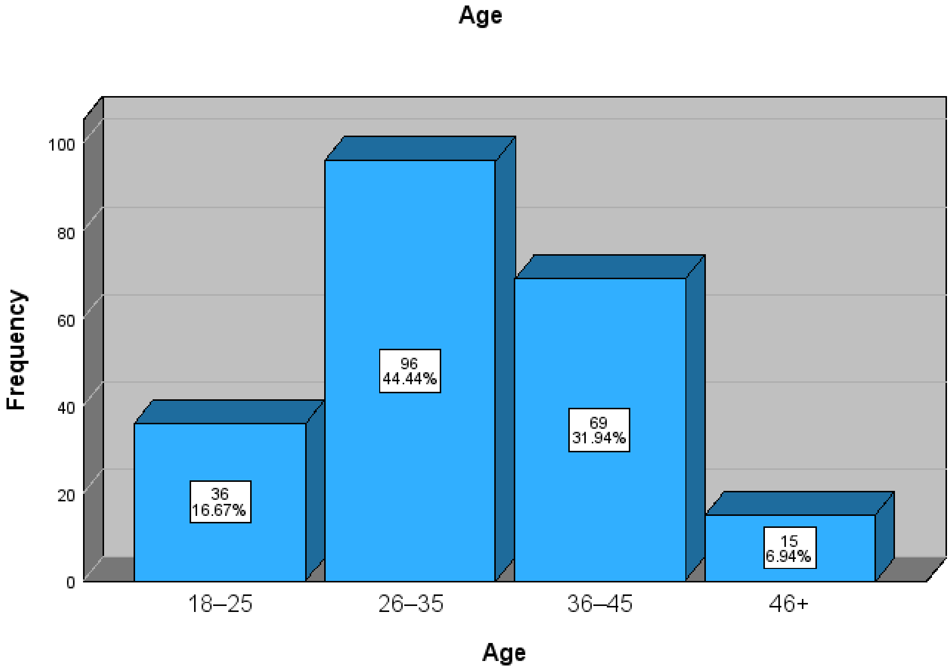

Figure 1: Age Distribution of Respondents

For gender, the sample is quite mixed. There are a bit more female participants (51.39%), while males make up 34.72%. Also, 13.89% didn't want to say their gender. So, there is a small difference, but it's not something very strong or one-sided.

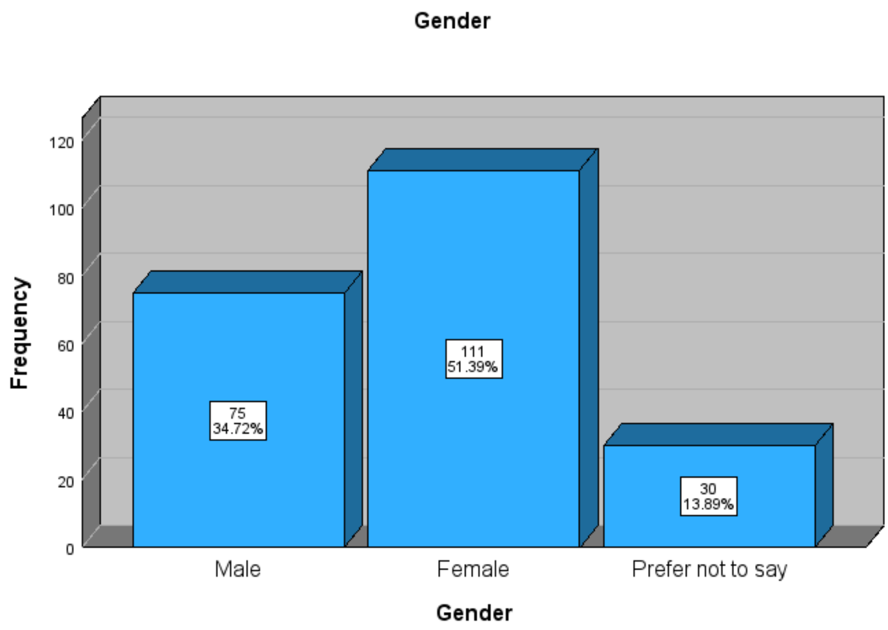

Figure 2: Gender Distribution of Respondents

For departments, the responses appear to be more widely distributed. A larger share comes from IT (29.17%), which is probably expected given the focus on AI. Finance follows with 22.22%, and then Operations at 19.44%. Human Resources makes up 15.28%, while Customer Service is lower at 8.33%. A small number of participants (5.56%) put "Other". Looking at this, there is clearly a stronger presence of people working in more technical or operational roles, especially IT. This actually fits quite well with the topic of the study, since these areas are more likely to deal with AI in practice.

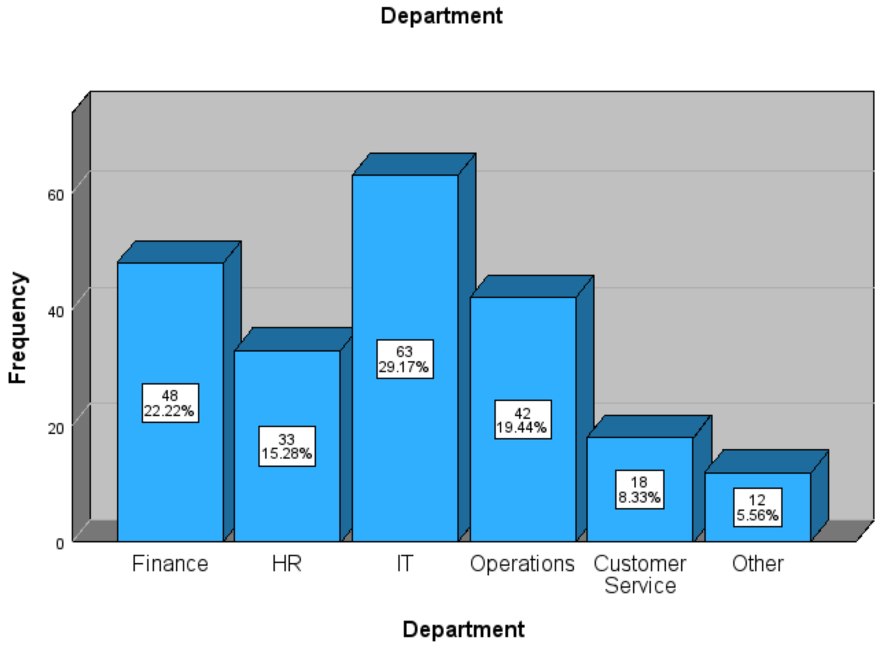

Figure 3: Departmental Distribution of Respondents

As for work experience, most of the participants are in the 2–5 year range, representing 50% of the sample. After that, those with 6–10 years make up 25%. The smallest groups are those with less than 2 years of experience (13.89%) and those with more than 10 years of experience (11.11%).

The sample looks to be a bit more evenly distributed across early to mid-career employees, which is more or less in line with what we saw earlier with age groups.

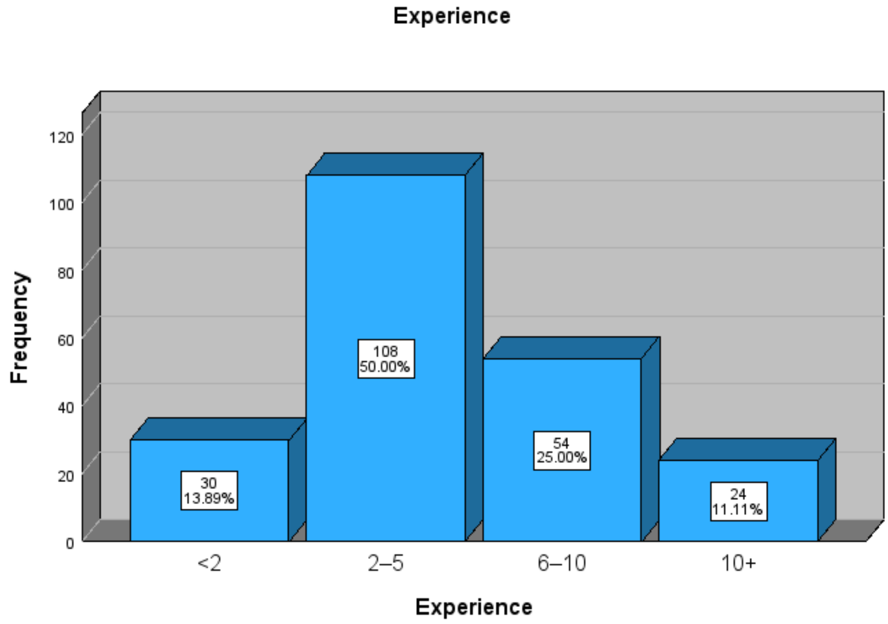

Figure 4: Years of Work Experience of Respondents

For company type, the sample is spread across different sectors. Finance has the largest share (33.33%), and telecommunications is quite close at 29.17%. Then comes pharmaceuticals with 19.44%, and the rest, about 18.06%, fall under other sectors.

So it's not concentrated in just one area, although there's clearly a bit more weight in finance and telecom. That probably makes sense given the topic, since these industries tend to be more active when it comes to AI.

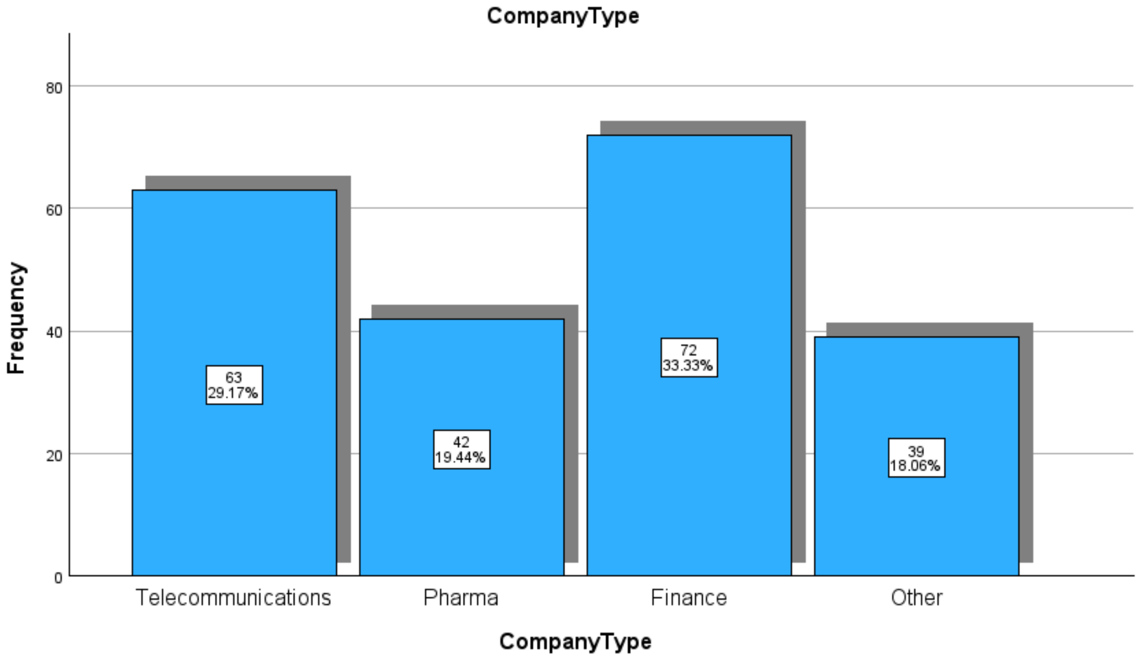

Figure 5: Company Type Distribution of Respondents

The findings suggest that generally people have a positive view of the use of AI in organizations. It seems that many respondents have the feeling that AI is something that already belongs to their daily work. For example, 63.9% agree or strongly agree that AI tools are part of their tasks, while 61.1% say that AI is used for key processes in the organization. A similar percentage (61.1%) also reports the use of AI systems as frequent or very frequent. Taken together, this suggests that AI is not simply there but is in fact routinely used in many workplaces.

At the same time, the support of the organization appears to be quite strong. Some 59.8% of respondents said their company encourages the use of AI technologies. This aligns with the general concept of digital transformation, where AI is playing an increasingly significant role across sectors. Also, neutral and some negative answers are present across the variables. This means that the picture is not entirely uniform. That could be because organizations are still in the early stages of adopting AI, or because there are practical challenges such as limited training or a lack of infrastructure.

Table 2: Distribution of Responses for AI Usage Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Integrated	2.8%	16.7%	16.7%	33.3%	30.6%
AI Use Frequency	0.0%	19.4%	19.4%	19.4%	41.7%
AI Key Processes	5.6%	11.1%	22.2%	26.4%	34.7%
AI Promoted	8.3%	12.5%	19.4%	18.1%	41.7%

The results indicate that employees see AI as beneficial in the workplace. Most agree or strongly agree that AI improves their performance at work (72.2%), increases productivity (70.8%) and helps them complete tasks faster (68.0%). It is worth noting that 52.8% strongly agree that AI appear to improve their performance, implying a particularly positive view of the impact of AI on their day-to-day work.

This is quite consistent with the main idea of the Technology Acceptance Model (TAM), where perceived usefulness is considered one of the main reasons for the adoption of technology by people. In this case, the responses indicate that many employees do see clear benefits to using AI in their work. Neutral responses especially in regard to the speed of the task (22.2%) at the same time indicate that the effect is not precisely the same for all. It might also depend on the type of work people do or how often they actually use AI systems. However, the overall picture is positive, and AI is seen more as a helpful tool than something that adds difficulty.

Table 3: Distribution of Responses for Perceived Usefulness Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Improves Performance	2.8%	6.9%	18.1%	19.4%	52.8%
AI Increases Productivity	4.2%	11.1%	13.9%	25.0%	45.8%

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Improves Speed	2.8%	6.9%	22.2%	23.6%	44.4%

The results show that employees overall see AI as relatively easy to use. The picture is a bit more nuance than with usefulness. Over half of the respondents agree or strongly agree that AI tools are easy to use (55.5%) and easy to learn (54.1%), while 59.7% feel that interaction with these systems is clear. Among these, clarity appears to be relatively more prominent, with 31.9% strongly agree that AI systems are understandable and user-friendly.
Likewise there are more neutral and negative responses here than in the previous results concerning usefulness. For example, a significant 29.2% of participants are neutral regarding the ease of learning AI. Further, about 22.2% of the respondents disagree to some extent that it is easy to use. This likely suggests that while employees see the benefits of AI, they don't always find it easy to use. It might also mean some people need more support or time to get used to these systems depending on their position or level of experience.

Table 4: Distribution of Responses for Ease of Use Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Easy to Use	6.9%	15.3%	22.2%	34.7%	20.8%
AI Easy to Learn	9.7%	6.9%	29.2%	22.2%	31.9%
AI Clear Interaction	2.8%	15.3%	22.2%	27.8%	31.9%

The results suggest that AI is broadly perceived as a useful tool in terms of efficiency. The majority of respondents agree it saves time in task completion (65.2%), improves accuracy (66.6%) and supports decision-making (66.6%). And an even larger percentage (73.6%) feel that AI impacts overall organizational performance. It's also interesting that over 40% strongly agree with this, which probably means that at least for some employees the impact is pretty noticeable.

But not all reactions are entirely positive at the same time. There still is a large share of the neutral responses, especially regarding decision-making (22.2%). This may indicate that AI is not being used consistently across all roles, or that some employees are not directly involved with it. So the overall picture is certainly positive, but the actual experience does seem to differ a little depending on the context.

Table 5: Distribution of Responses for Operational Efficiency Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Reduces Time	1.4%	16.7%	16.7%	31.9%	33.3%
AI Improves Accuracy	4.2%	13.9%	15.3%	31.9%	34.7%
AI Enhances Decision-Making	2.8%	8.3%	22.2%	34.7%	31.9%
AI Improves Org Performance	1.4%	9.7%	15.3%	33.3%	40.3%

The results suggest that AI is perceived as a job changer rather than a job replacer. Most of the respondents agree that AI has changed the way they work (65.3%) and increased the level of task automation (68.0%) Plus, 70.8% say AI allows them to spend more time on complex or higher-value work. That seems to back up the idea that AI is serving more as a helpful tool rather than a complete replacement for roles.

But on the question of job loss, the answers seem to be quite different. 59.7% of the participants disagree that AI reduces the need for jobs, while a smaller group (15.3%) believe it directly leads to fewer roles. So while people can see AI is changing the way work is done, they don't really see it as an immediate threat to employment. It is more of a task shifting tool than a completely workforce replacement.

Table 6: Distribution of Responses for Workforce Impact Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Changes Job	4.2%	19.4%	11.1%	27.8%	37.5%
AI Task Automation	4.2%	8.3%	19.4%	34.7%	33.3%
AI Enables Complex Work	4.2%	9.7%	15.3%	34.7%	36.1%
AI Reduces Roles	27.8%	31.9%	25.0%	9.7%	5.6%

The answers indicate that employees, in general, are confident about AI systems. The majority of participants trust the outputs (68.0%) and consider these systems reliable (62.5%). Also, some 69.5% say they are comfortable relying on AI in their work. Overall, there is a relatively high level of confidence in using AI for day to day tasks and decisions. That said transparency doesn't appear to be as strong. A little more than half of the respondents (52.7%) agree that AI systems are transparent, but a significant proportion are neutral (25.0%) or even disagree (22.3%). This suggests a more varied pattern. People seem willing to trust and use AI, but at the same time they are not always sure how it works in practice. The employees may accept the results without knowing the process.

Table 7: Distribution of Responses for Trust in AI Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Trust Outputs	5.6%	15.3%	11.1%	36.1%	31.9%
AI Reliable	4.2%	16.7%	16.7%	25.0%	37.5%
AI Transparent	5.6%	16.7%	25.0%	33.3%	19.4%
AI Comfort in Use	2.8%	12.5%	15.3%	27.8%	41.7%

The results are not entirely consistent regarding fear and resistance. On one hand, quite a few respondents do seem to worry about job replacement, with 59.7% agreeing that AI could replace their job. So there is clearly some concern at a general level.

At the same time though, other responses don't fully match that level of concern. Most participants actually disagree that they feel uncertain about their future role (68.0%), and many also don't prefer human judgment over AI (62.5%). In addition, more than half (52.7%) say they don't hesitate much when it comes to using AI tools.

Putting these together, it seems that even if people have some worries in theory, this doesn't necessarily affect how they behave in practice. They still appear quite open to using AI and don't seem strongly resistant to it. So the concern is there, but it's not really translating into avoidance or rejection of the technology.

Table 8: Distribution of Responses for Fear & Resistance Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Job Fear	5.6%	9.7%	25.0%	31.9%	27.8%
AI Uncertainty	31.9%	36.1%	11.1%	15.3%	5.6%
Prefer Human over AI	37.5%	25.0%	16.7%	16.7%	4.2%
AI Hesitation	19.4%	33.3%	25.0%	16.7%	5.6%

The results indicate that employees generally feel supported by their organizations in relation to AI. A large proportion believe that management supports the use of AI (69.4%) and that they feel supported in their use of these systems in their work (65.3%). Similarly, a large percentage of respondents (68.1%) report that their organizations promote digital upskilling, which is a more active effort to prepare employees to work with AI.

Taking all the above into account, training does seem to be the one area where the answers are a little less strong. Most of the respondents (55.6%) agree that the training given is sufficient but there is still a large percentage that is either neutral (26.4%) or slightly dissatisfied (18.1%). So, the findings are not entirely consistent.. Organizations seem to be supportive of AI and usually promote the use of it by employees, but structured training may not always be as consistent as one would think. There may be training available, but it may not be what employees need or it may differ by department or position.

Table 9: Distribution of Responses for Organizational Support Variables (%)

Variable	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
AI Training Provided	5.6%	12.5%	26.4%	29.2%	26.4%
Management Support	2.8%	9.7%	18.1%	36.1%	33.3%
Support in AI Use	1.4%	15.3%	18.1%	27.8%	37.5%
Encouragement Upskilling	4.2%	9.7%	18.1%	27.8%	40.3%

Regarding the descriptive statistics, the main variables of the study display a rather clear pattern. In general, most of the mean values are higher suggesting that respondents tend to hold quite positive views on AI. The highest means are for Perceived Usefulness (M=4.03) followed by Operational Efficiency (M=3.86) and Organizational Support (M=3.80). This suggests that employees not only see AI as useful, but they also associate it with better performance and view their organizations as generally supportive of its use. Likewise, the AI Usage (M = 3.75) and the Trust in AI (M = 3.72) are very high, indicating a fairly regular use of AI and a generally positive level of trust in these systems.

Some of the other variables are a little lower, but not necessarily low. Ease of Use (M = 3.59) and Workforce Impact (M = 3.45) seem to be more moderate, which likely represents a moderately positive, but not as strong employee sentiment as in the previous areas. The mean lowest is in Fear and Resistance (M=2.68) which is quite interesting since this suggests that concern or resistance to AI is not very high in this sample.

Considering the spread of the data, the values of the standard deviation are mostly in an acceptable range, so the responses do not seem to be extremely scattered. There’s some variation but nothing that’s worrying. The distribution of most of the variables is negatively skewed. Generally, this means responses are more concentrated at agreement or higher on the scale. However, Fear and Resistance has a positive skew (Skewness = 0.417) as expected, owing to its lower mean, so the responses are more concentrated toward lower values. Kurtosis values seem fine too, so there are no large signs of unusual distribution patterns.

Generally, these descriptions indicate a positive disposition toward AI on the part of the respondents. Fear or resistance is relatively low, while the advantages are very clear to employees.

Table 10: Descriptive Statistics of Key Research Variables

Descriptive Statistics	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
AI_Usage	216	1.5	5	3.7535	1.04115	-0.745	-0.761
Perceived_Usefulness	216	1.67	5	4.0328	0.98671	-0.986	-0.076
Ease_of_Use	216	1.33	5	3.5925	1.0413	-0.627	-0.694
Operational_Efficiency	216	1.5	5	3.8611	0.92342	-0.62	-0.532
Workforce_Impact	216	2	4.25	3.4549	0.57465	-0.598	-0.498
Trust_AI	216	1.75	5	3.7153	1.03343	-0.622	-1.077
Fear_Resistance	216	1.5	4	2.684	0.63611	0.417	-1.059

Org_Support	216	1.75	5	3.8021	0.95504	-0.706	-0.735

4.2 Differentiations

Any age-related differences in the main study variables were tested using the Kruskal–Wallis H test. The test explored AI use, perceived usefulness, ease of use, operational efficiency, workforce impact, trust in AI, fear and resistance, and organizational support.

The results suggest age does seem to matter in some ways. Statistically significant differences were observed for AI usage ($H = 7.859$, $p = 0.049$), operational efficiency ($H = 9.912$, $p = 0.019$), workforce impact ($H = 10.130$, $p = 0.017$), trust in AI ($H = 17.603$, $p < 0.001$), fear and resistance ($H = 18.607$, $p < 0.001$), and organizational support ($H = 15.600$, $p = 0.001$). This indicates that age is related to the employees' experience of AI, especially in terms that go beyond the use of the system and are more related to trust, perceived impact, and support from the organization.

Not all variables change by age group simultaneously. There were no significant differences in perceived usefulness ($H = 3.434$, $p = 0.329$) and ease of use ($H = 6.983$, $p = 0.072$). So, although employees of different ages may not have exactly the same reaction to AI in general, they appear to be quite similar in their assessment of whether AI is useful or easy to use.

The difference is that the more basic assessments of AI are quite stable, while the more experience-related or attitudinal aspects appear to change more clearly with age. In other words, employees may agree on the practical benefits of AI but differ on trust, perceived risk or the type of support they think they are receiving. This could indicate a generational element to how people understand and experience AI at work.

Table 11: Kruskal–Wallis Test Results for Differences Across Age Groups

b Grouping Variable: Age	AI_Usage	Perceived_Usefulness	Ease_of_Use	Operational_Efficiency	Workforce_Impact	Trust_AI	Fear_Resistance	Org_Support
Kruskal-Wallis H	7.859	3.434	6.983	9.912	10.13	17.603	18.607	15.6
df	3	3	3	3	3	3	3	3
Asymp. Sig.	0.049	0.329	0.072	0.019	0.017	<.001	<.001	0.001

A Kruskal-Wallis H test was also conducted to determine if gender makes a difference in the main variables within the study. Variables included AI Use, Perceived Usefulness, Ease of Use, Operational Efficiency, Workforce Impact, Trust in AI, Fear and Resistance, and Organizational Support.

The results indicate that gender could be a factor in some areas but not in all. Statistically significant differences are found in perceived usefulness ($H = 8.740$, $p = 0.013$), ease of use ($H = 7.610$, $p = 0.022$) and operational efficiency ($H = 10.855$, $p = 0.004$). So, there seem to be some differences in usefulness, ease of use and performance improvement from AI between male and female respondents.

The differences in the remaining variables, however, are not statistically significant. This includes usage of AI ($H = 2.752$, $p = 0.253$), impact on workforce ($H = 2.150$, $p = 0.341$), trust on AI ($H = 3.249$, $p = 0.197$), fear and resistance ($H = 2.287$, $p = 0.319$) and organizational support ($H = 2.821$, $p = 0.244$). Responses seem to be quite similar in these cases regardless of gender.

The key here is the variation across the more pragmatic or evaluative dimensions of AI (e.g., usefulness, ease of use) but not in the broader attitudes of trust, resistance or general usage. This may indicate that differences between genders are more prominent in the context of performance experience of AI, rather than general acceptance or intention to use.

Table 12: Kruskal–Wallis H Test for Differences in Key Variables by Gender

b Grouping Variable: Gender	AI_Usage	Perceived_Usefulness	Ease_of_Use	Operational_Efficiency	Workforce_Impact	Trust_AI	Fear_Resistance	Org_Support
Kruskal-Wallis H	2.752	8.74	7.61	10.855	2.15	3.249	2.287	2.821
df	2	2	2	2	2	2	2	2
Asymp. Sig.	0.253	0.013	0.022	0.004	0.341	0.197	0.319	0.244

A Kruskal–Wallis H test was used to test for departmental differences in the main variables in the study. These were AI use, perceived usefulness, ease of use, operational efficiency, workforce impact, trust in AI, fear and resistance, and organizational support.

Looking at the results, department seems to matter quite a bit in most of these areas. There were statistically significant differences for AI usage ($H = 14.634$, $p = 0.012$), perceived usefulness ($H = 18.677$, $p = 0.002$), ease of use ($H = 16.692$, $p = 0.005$), operational efficiency ($H = 17.704$, $p = 0.003$), trust in AI ($H = 26.532$, $p < 0.001$), fear and resistance ($H = 22.042$, $p < 0.001$), and organizational support ($H = 20.428$, $p = 0.001$). So in conclusion, it would seem that employees in different departments do not seem to experience or evaluate AI in the same way.

Interestingly, workforce impact ($H = 10.499$, $p = 0.062$) is not statistically significant, although it is close to the conventional significance threshold. This may suggest that departments may have comparable views about the impact of AI on their occupation, even though they may have different attitudes towards the use or assessment of AI.

What is remarkable is that most of the variation is in areas related to daily use, perception and support. This might have to do with the kind of work people do in each department. For instance, IT or Operations people might have a more direct contact with AI systems which may shape their views differently than functions like HR or Finance. So the difference between departments is probably more about differences in exposure and day to day experience rather than totally different attitudes towards AI overall.

Table 13: Kruskal–Wallis H Test for Differences in Key Variables by Department

b Grouping Variable: Department	AI_Usage	Perceived_Usefulness	Ease_of_Use	Operational_Efficiency	Workforce_Impact	Trust_AI	Fear_Resistance	Org_Support
Kruskal-Wallis H	14.634	18.677	16.692	17.704	10.499	26.532	22.042	20.428
df	5	5	5	5	5	5	5	5
Asymp. Sig.	0.012	0.002	0.005	0.003	0.062	<.001	<.001	0.001

In order to check whether experience levels make a difference across the main variables in the study, Kruskal–Wallis H test was used. These were AI usage, perceived usefulness, ease of use, operational efficiency, impact on workforce, trust in AI, fear and resistance, and organizational support.

When we review the results, it looks like experience is really important in a couple of places. We found a significant difference in AI usage ($H=29.106$, $p<0.001$) indicating that employees with different experience levels do not interact with AI the same way. Furthermore, ease of use ($H = 14.561$, $p = 0.002$), operational efficiency ($H = 14.141$, $p = 0.003$), impact on the workforce ($H = 8.821$, $p = 0.032$), trust in AI ($H = 11.921$, $p = 0.008$), fear and resistance ($H = 12.571$, $p = 0.006$) and organizational support ($H = 12.848$, $p = 0.005$) are statistically significant. This all suggests that experience is not just about how often AI is used, but how it is understood.

However, perceived usefulness ($H = 6.559$, $p = 0.087$) does not significantly differ among experience groups. Thus, while employees may disagree about how AI is used and evaluated in practice, they appear to be in agreement that it is valuable.

What is really interesting here is that usefulness is rather stable, while the more practical or experience-based things, such as usage, trust or resistance, vary more distinctly. This likely means that experience influences how people interact with AI and how comfortable they are with it, rather than whether they see the benefits of AI in general.

Table 14:Kruskal–Wallis H Test for Differences in Key Variables by Years of Experience

b Grouping Variable: Experience	AI_Usage	Perceived_Usefulness	Ease_of_Use	Operational_Efficiency	Workforce_Impact	Trust_AI	Fear_Resistance	Org_Support
Kruskal-Wallis H	29.106	6.559	14.561	14.141	8.821	11.921	12.571	12.848
df	3	3	3	3	3	3	3	3
Asymp. Sig.	<.001	0.087	0.002	0.003	0.032	0.008	0.006	0.005

Kruskal Wallis H test was also employed to find out whether the type of company makes a difference in the main variables of the study. These were AI usage, perceived usefulness, ease of use, operational efficiency, workforce impact, trust in AI, fear and resistance, and organizational support.

The results are slightly different but only in certain areas. Particularly, perceived usefulness ($H = 7.968$, $p = 0.047$) and operational efficiency ($H = 12.136$, $p = 0.007$) show significant differences across industries. From the results, it looks like there are some differences, but only in certain areas. In particular, perceived usefulness ($H = 7.968$, $p = 0.047$) and operational efficiency ($H = 12.136$, $p = 0.007$) show statistically significant variation across industries. This suggests that employees in different sectors don't always evaluate AI in the same way when it comes to its value or its contribution to performance.

This indicates that employees from different sectors do not necessarily evaluate AI in the same way in terms of its value or its contribution to performance.

However, the differences for the other variables are not statistically significant. This is the case for the AI usage ($H=4.545$, $p=0.208$), ease of use ($H=0.885$, $p=0.829$), workforce impact ($H=6.060$, $p=0.109$), trust in AI ($H=4.651$, $p=0.199$), fear and resistance ($H=4.909$, $p=0.179$) and organizational support ($H=3.777$, $p=0.287$). So in these areas, answers seem similar across industries.

It seems that the basic aspects of AI adoption do not change much between sectors, such as whether people use it or trust it. But we have some differences in the way we judge the effectiveness or value of AI. This may have to do with how AI is actually used in various industries, for example telecom, finance or pharmaceuticals where the level of digital maturity and the type of work can vary quite a lot.

Table 15: Kruskal–Wallis H Test for Differences in Key Variables by Company Type

b Grouping Variable: CompanyType	AI_Usage	Perceived_Usefulness	Ease_of_Use	Operational_Efficiency	Workforce_Impact	Trust_AI	Fear_Resistance	Org_Support
Kruskal-Wallis H	4.545	7.968	0.885	12.136	6.06	4.651	4.909	3.777
df	3	3	3	3	3	3	3	3
Asymp. Sig.	0.208	0.047	0.829	0.007	0.109	0.199	0.179	0.287

4.3 Correlations

The correlation between the main variables of the study was studied with Spearman's rank-order correlation analysis. Factors were AI usage, perceived usefulness, ease of use, operational efficiency, workforce impact, trust in AI, fear and resistance, and organizational support.

The results show that most of these variables are strongly and positively correlated. For example, adoption of AI is significantly positively correlated with operational efficiency ($\rho = 0.795$, $p < 0.001$), perceived usefulness ($\rho = 0.749$, $p < 0.001$) and perceived ease of use ($\rho = 0.766$, $p < 0.001$). This seems to suggest that the more AI is used, the more likely employees are to consider it more useful, easier to use, and more likely to lead to efficiency. Similarly, trust in AI is positively and significantly correlated with operational efficiency ($\rho = 0.829$, $p < 0.001$), perceived usefulness ($\rho = 0.815$, $p < 0.001$), and AI usage ($\rho = 0.802$, $p < 0.001$). So trust seems to be really important in how positive an experience is overall with AI.

Organizational support has a very similar picture. It has strong positive correlation with almost all other variables especially AI usage ($\rho = 0.849$, $p < 0.001$), operational efficiency ($\rho = 0.845$, $p < 0.001$), and trust in AI ($\rho = 0.844$, $p < 0.001$). This probably means that when employees feel their organization has their back they are more likely to use AI, trust it and see benefits from it. There are also strong positive associations with the impact on the workforce, in particular with perceived usefulness ($\rho = 0.749$, $p < 0.001$) and trust in AI ($\rho = 0.763$, $p < 0.001$), which may suggest that job-related changes are not necessarily perceived negatively, but can also be associated with positive perceptions of AI.

The only variable that moves in the opposite direction is fear and resistance. Here the correlations are generally strong and negative. The most negative correlation is observed with trust in AI ($\rho = -0.906$, $p < 0.001$) followed by operational efficiency ($\rho = -0.741$, $p < 0.001$) and AI usage ($\rho = -0.698$, $p < 0.001$). All in all, the higher the fear or resistance reported by employees, the less likely they are to trust AI, use it regularly, or view it as beneficial. One of the most obvious patterns in the correlation analysis.

Table 16: Spearman Correlation Matrix of Key Research Variables

Correlations	Spearman's rho	Perceived_Usefulness	Ease_of_Use	Operational_Efficiency	Workforce_Impact	Trust_AI	Fear_Resistance
AI_Usage	Correlation Coefficient						
	Sig. (2-tailed)						
Perceived_Usefulness	Correlation Coefficient	--					
	Sig. (2-tailed)	.					
Ease_of_Use	Correlation Coefficient	.775**	--				

	Sig. (2-tailed)	<.001	.				
Operational_Efficiency	Correlation Coefficient	.817**	.775**	--			
	Sig. (2-tailed)	<.001	<.001	.			
Workforce_Impact	Correlation Coefficient	.749**	.738**	.704**	--		
	Sig. (2-tailed)	<.001	<.001	<.001	.		
Trust_AI	Correlation Coefficient	.815**	.815**	.829**	.763**	--	
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	.	
Fear_Resistance	Correlation Coefficient	-.776**	-.702**	-.741**	-.781**	-.906**	--
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	.
Org_Support	Correlation	.807**	.821**	.845**	.770**	.844**	-.778**

	Coefficient						
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001

4.4 Regression

A multiple linear regression was conducted to examine the extent to which factors such as AI usage, perceived usefulness, ease of use, trust in AI and organizational support predict operational efficiency.

The overall model was statistically significant ($F(5,210) = 184.297$, $p < 0.001$), which essentially means that these variables, when taken together, are good at predicting operational efficiency. The value of R 2 is quite high (0.814), with an adjusted R 2 of 0.810, so about 81% of the variation in operational efficiency can be explained by this model. This is relatively high and suggests that the model fits the data well.

Looking at the individual variables, organizational support is the most significant ($\beta = 0.360$, $p < 0.001$). In practical terms this seems to mean that when employees feel supported by their organization, they report also higher levels of efficiency. Perceived usefulness ($\beta = 0.229$, $p < 0.001$) and AI usage ($\beta = 0.218$, $p = 0.001$) were also significant, indicating that both seeing AI as useful and actually using AI are associated with better performance outcomes.

Conversely, ease of use ($\beta = 0.110$, $p = 0.123$) and trust in AI ($\beta = 0.040$, $p = 0.634$) do not seem to have a direct effect in this model. Interesting, since previous results showed that they are related at correlational level, but here their influence seems weaker when all variables are considered together.

So overall, it looks like organizational factors and actual usage are more important in explaining efficiency than just how easy or trustworthy the system feels to use. In other words, the right environment and actually working with the AI seem to play a bigger role than positive perceptions alone.

Table 17: Multiple Regression Model Summary for Operational Efficiency

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.902a	.814	.810	.40253
a. Predictors: (Constant), Perceived_Usefulness, AI_Usage, Org_Support, Ease_of_Use, Trust_AI				

Table 18: ANOVA Results for the Regression Model

ANOVAa						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	149.307	5	29.861	184.297	<.001b
	Residual	34.026	210	.162		
	Total	183.333	215			
a. Dependent Variable: Operational_Efficiency						
b. Predictors: (Constant), Perceived_Usefulness, AI_Usage, Org_Support, Ease_of_Use, Trust_AI						

Table 19: Regression Coefficients for Operational Efficiency

Coefficientsa						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.465	.121		3.831	<.001

	AI_Usage	.193	.058	.218	3.314	.001
	Trust_AI	.036	.075	.040	.477	.634
	Ease_of_Use	.097	.063	.110	1.547	.123
	Org_Support	.348	.078	.360	4.467	<.001
	Perceived_Usefulness	.215	.063	.229	3.420	<.001
a. Dependent Variable: Operational_Efficiency						

We used a multiple linear regression to investigate the relationship between AI use, AI trust, fear and resistance with impact on the workforce.

The model overall is statistically significant ($F(3,212) = 162.288$, $p < 0.001$), so these variables do seem to explain workforce impact quite well. The R^2 is 0.697 (adjusted $R^2 = 0.692$) which means that this explains about 69% of the variation in workforce impact. That is a pretty good result, so the model seems to fit the data fairly well.

One result, when you break it down, is pretty clear. Fear and resistance had a strong negative effect ($\beta = -.562$, $p < .001$). In short: The more people are worried about AI, the less positive they feel about job change. This seems pretty intuitive, but the effect size here is quite significant compared to the other variables.

The other two predictors are less clear cut. AI use ($\beta = 0.154$, $p = 0.054$) is marginally significant. So there might be some correlation but not enough to be confident about. Trust in AI ($\beta = 0.159$, $p = 0.253$) was not a significant effect in this model, although earlier results indicated a relation.

All in all, what comes out of all of this is that fear and resistance seem to be more important than the other factors in terms of workforce impact. Even if staff are using AI or have some degree of trust in it, negative feelings seem to outweigh their perception of changes to their jobs. This suggests that tackling concerns about AI might be just as, or even more, important than simply increasing use or trust.

Table 20: Multiple Regression Model Summary for Workforce Impact

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.835a	.697	.692	.31873
a. Predictors: (Constant), Fear_Resistance, AI_Usage, Trust_AI				

Table 21: ANOVA Results for Workforce Impact Model

ANOVAa						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	49.460	3	16.487	162.288	<.001b
	Residual	21.537	212	.102		
	Total	70.997	215			
a. Dependent Variable: Workforce_Impact						
b. Predictors: (Constant), Fear_Resistance, AI_Usage, Trust_AI						

Table 22: Regression Coefficients for Workforce Impact

Coefficientsa					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		

1	(Constant)	4.168	.439		9.504	<.001
	AI_Usage	.085	.044	.154	1.935	.054
	Trust_AI	.089	.077	.159	1.147	.253
	Fear_Resistance	-.507	.092	-.562	-5.535	<.001
a. Dependent Variable: Workforce_Impact						

5 DISCUSSION

5.1 Interpretation of Key Findings

A broadly positive picture emerges from the findings, although it would be too simplistic to describe employee attitudes toward AI as uniformly positive. What stands out first is how embedded AI already seems to be in everyday work. Many respondents reported that they use AI tools regularly and that these tools are involved in core processes rather than side activities. This points to a level of adoption that appears to go beyond innovative experimentation, and it has been integrated into daily workflows. At the same time, this should be interpreted carefully, since the findings reflect employee perceptions and not an objective measure of technological maturity across firms.

Perceived usefulness was one of the strongest dimensions in the study, and this is probably one of the clearest indications of why AI is being accepted in practice. This positive perception could also be affected by the general tendency of the organization to constantly highlight the benefits of AI and not be purely based on actual personal experience. Many respondents associated AI with better performance, higher productivity, and faster task completion. This is not especially surprising, and the strength of the responses does suggest that employees are not viewing AI as a minor support tool. For a considerable part of the sample, it seems to be something that meaningfully changes how work gets done. Still, the neutral responses should not be overlooked. They suggest that these benefits are not experienced in the same way by everyone. This may reflect differences in job role, level of exposure to AI, or how mature AI use actually is within different departments.

Another possible explanation could be that employees evaluate AI based on its practical outcomes rather than on the technology itself. When AI helps employees complete their tasks faster or more effectively, perceptions of usefulness are more likely to increase regardless of how sophisticated the underlying technology may be. This may explain why perceived usefulness emerged as one of the strongest constructs in the study.

The story is a little more mixed on the ease of use, and this contrast is important. Employees seem more convinced of the usefulness of AI than of its ease of use. In other words, they may see its value even if it's not always easy to use it. This is important because it indicates that adoption is not solely a matter of how easy the tools are, but also whether employees perceive the tools to be helpful in tangible ways. One possible explanation is that some users have learnt how to overcome usability issues through experience, peer support or repeated exposure. This may also give an explanation for the relatively lower rating of formal ease of use as compared to usefulness.

The results on operational efficiency were also clearly positive, as many respondents associated AI with time savings, better accuracy and improved decision making. What is important to note here, however, is that these are perceived improvements, not measured performance outcomes. That does not make them unimportant, but it does mean that they should be interpreted with caution. Employees can really believe AI makes work more efficient, but that's not the same as showing objective gains at the organizational level. However, the fact that this pattern is present across a number of indicators suggests that employees are seeing changes in the way work is done, not just in isolated tasks, but more broadly across workflows. On the other hand, there are some remaining neutral responses especially in the field of decision-making. This may mean that AI has a larger impact on some positions than others, or that its impact is more visible in some types of tasks. While respondents strongly believe that AI improves efficiency, future research could validate based on measurable improvements around productivity, accuracy, or organizational performance if these perceptions are accurate.

The workforce findings are perhaps the most interesting, as they tell a more ambivalent story. On the one hand, employees seem to be aware that AI is changing job content and increasing automation. On the other hand, many say it frees them to focus on more complicated, higher-value work. This supports the idea that AI is more often experienced as a job reconfiguration rather than a direct replacement (Acemoglu & Restrepo, 2020). That's not to say employees feel perfectly secure, and the data also continues to show concerns about potential job loss in the future. Also, this could indicate that this situation created expectations to the employees for future job changes and upgrade, that go beyond their current experience with AI.

This creates clear tension since employees are able to identify and highlight the benefits AI brings at the moment, but they remain insecure about what consequences this could have in the future. This contradiction suggests that employees may view AI as both an opportunity and a threat at the same time. While AI creates opportunities and gives employees more space for more complex and valuable work, it may also bring uncertainty about future career modification and job security. The existence of both perceptions highlights the complexity of workforce reactions to technological change.

A similar tension appears in relation to trust. Overall, respondents reported relatively high trust in AI outputs and a fairly strong level of comfort in using these systems. Transparency, however, presented a lower score. This could indicate that employees might be open to trust AI even when they do not completely understand how it works. In practice this may not be a problem, at least not in the short-term, particularly when the systems are being used for routine support tasks (Glikson & Woolley, 2020). This finding brings a challenge to the organizations since employees may support AI implementation in the short-term, but insufficient transparency could create confusion and concerns future wise.

The results of the section fear and resistance add another layer to this picture. It can be concluded that the worries about job replacement are clearly strong, yet more active forms of resistance seem much weaker. Respondents did not strongly report avoiding AI, resisting it, or consistently preferring human judgment. This may mean that concern about AI does not automatically lead to rejection of it. One possible explanation is that employees distinguish between short-term usefulness and long-term uncertainty. Another is that in many workplaces AI is already integrated enough that refusing to engage with it is not a realistic option. The results therefore suggest that fear is not automatically linked to resistance. Employees recognize the benefits of AI but at the same time they feel insecure about its future implications.

Finally, organizational support appears to be one of the more important contextual factors in the study. Many respondents felt that their organizations support AI use and encourage upskilling, which may partly explain the generally positive attitudes reported. Even so, training seems to be the weaker part of that support. Employees appear to feel encouraged to use AI, but not always equally prepared for it. This may be one reason why usefulness scores were stronger than ease of use scores. This suggests that organizations may be creating a generally supportive environment for AI adoption, but not always backing that up with sufficiently structured learning opportunities. That gap may become more important over time, especially if AI systems become more complex or more central to decision-making. Overall, we can conclude that successful AI adoption depends not only on the technology itself but also on the path the organization will follow. Supportive leadership, access to resources, and continuous learning opportunities may be just as important as technical capabilities in the employees' reactions to it.

5.2 Comparison with Literature

The findings of this study generally follow the literature on AI adoption in multinational corporations, especially when it comes around productivity and operational efficiency. The positive contribution of AI to performance, accuracy, and time saving is consistent with the previous studies showing that AI usage can be highly connected with efficiency. Studies have found that automation and data-driven systems can successfully reduce errors, make processes more efficient and positively support decision-making (Brynjolfsson et al., 2025; Davenport & Mittal, 2023). In this sense, the results are more or less expected and confirm H1 and H2. However, the findings also suggest that employee perceptions may play a more important role than is often acknowledged in literature. While previous studies focus more on objective organizational outcomes, the current findings show that perceived improvements in productivity and efficiency may themselves influence the acceptance and continued use of AI.

A further contribution of this study that is more unique is the emphasis on how these outcomes are experienced at the employee level. The bulk of the literature on AI adoption is at the organizational or strategic level whereas this study zooms in on everyday work practices. This points to the fact that gains in efficiency are not just technical outcomes but are also shaped by how employees interact with AI in their day-to-day work. In this sense, the findings confirm previous claims that AI adoption is more meaningful when embedded in routine work processes than as a standalone tool (Raisch & Krakowski, 2021). Consequently, the results confirm previous studies but also bring them closer to the level of everyday work experience. This contribution is important because successful AI implementation is directly connected to employee engagement and acceptance. If employees do not handle AI as a useful tool for their daily work, even high efficiency AI systems may not be able to bring the benefits they could.

The results on the impact on the workforce also tend to be consistent with what we already know, particularly regarding task based theories of technological transformation. The fact that there is a tendency to automate repetitive tasks and provide higher value work to the employees confirms the argument that the impact of technology is more about reshaping jobs than eliminating jobs (Acemoglu & Restrepo, 2020), which is consistent with H3.

This combination of feelings including positive perceptions and at the same time intense concern is also reflected in prior studies that suggest technological change often results in a feeling of uncertainty even when the short-term effects are not negative (Brougham & Haar, 2018). Thus, rather than contradicting the literature, we can conclude that the present findings enforce the previous statements, showing that both views can exist. This combination of feelings may represent a temporary attitude since many organizations are still on a transitional stage regarding AI adoption.

Technology acceptance outcomes are also consistent with established models such as TAM. Perceived usefulness is a significant determinant of H4, confirming that the more employees perceive the value of AI, the more likely they are to adopt AI (Venkatesh et al., 2012). At the same time ease of use seems to be a less important factor, which is an interesting point. It suggests that users may be prepared to accept usability problems if they find the benefits to be high. This does not contradict TAM, but it may suggest that usefulness is more important than ease of use in the AI context. This finding strengthens arguments that perceived usefulness represents the main factor of technology acceptance in workplace.

Trust also has an important role in more recent extensions of technology acceptance models. The relatively high levels of trust reported in the study support H5 and are congruent with research that has shown that confidence in AI systems is important for adoption (Glikson & Woolley, 2020). But the lower levels of perceived transparency suggest a more complex relationship. Employees appear to be willing to trust AI even if they don't fully understand how it works. This may be a consequence of the role of organizational context, or repeated use, but it raises questions as to the long-term sustainability of such trust, especially in more critical or high impact situations. This can indicate except from technical transparency, the organizational culture, prior experience with AI systems, and managerial support may also play a significant role when it comes to trust.

The results on fear and resistance are in agreement and disagreement with literature. Concerns about job displacement were apparent, confirming previous research (Brougham & Haar, 2018). However, actual resistance to AI seemed to be fairly limited. It is important to highlight that employees did not report strong opposition to AI or avoidance of its use. This can be translated that fear does not automatically connect with behavioral resistance, which adds a more detailed view to the existing assumptions in literature. The negative relation between fear and acceptance is consistent with H6, but the gap between concern and action reveals a more complex dynamic in practice.

Organizational support also can be considered an important factor, and it matches with previous studies that emphasize facilitating conditions (Venkatesh et al., 2012). Employees who feel they receive support from management level, and feel encouraged to develop their skills, tend to report more positive attitudes toward AI. Based on the findings it can be concluded that organizational support may help to reduce uncertainty, strengthen trust, and increase employees' willingness to work with AI tools. This broader role of organizational support deserves greater investigation in future research.

Finally, the results regarding the multinational corporations are in alignment with the literature, indicating more structured and coordinated approaches to AI implementation. The high levels of AI usage and at the same time positive perceptions suggest that these organizations most probably have proceeded beyond initial experimentation. This aligns with findings that firms with more developed infrastructures and coordinated strategies tend to have more consistent results with AI (Jöhnk et al., 2021). However, these findings should be interpreted with caution, as the sample consists primarily of employees working in organizations where AI has already been implemented, and employees may have more positive perceptions than in other organizations where AI is still in transitional stage.

5.3 Implications for Multinational Management

The results of this study have several practical implications for managers working in multinational corporations, especially regarding the introduction and use of AI across different organization units. And one of the main things that comes out quite clearly is that AI is no longer a technical issue. It seems to require continuous alignment on the management level as it encompasses not only systems and data but also how people work, what they expect and how processes are designed. The findings show relatively high levels of AI usage, suggesting that successful adoption happens when AI is integrated into daily work, rather than being an add-on to existing processes. It could be therefore essential for managers to pay equal attention to organizational culture, employee engagement, and change management together with the technological infrastructure and system performance. This is especially the case with multinational organizations that face the problem of reconciling standardization with flexibility. We work in different countries, different contexts, so it’s unlikely that one approach will work everywhere. A more realistic approach for firms may be to adopt a hybrid model. In this model core systems and data structures are designed centrally but some level of local adaptation is allowed. That could help ensure consistency in areas such as governance and data quality and ensure the relevance of AI tools in different local contexts. However, balancing global consistency with local adaptation may present significant managerial challenges since extreme standardization could not be effective for specific markets, while excessive decentralization could create inconsistencies in governance, data management, and compliance practices.

Another point is the way decisions are made. The findings point to the fact that AI is increasingly being used to support decision making, potentially making things faster and more data-driven. It does not mean the managers will be replaced but their role may slowly evolve. It is they who have to interpret the AI’s outputs and decide how much weight to assign to them, not just decide for themselves. Longer term, this may mean a more distributed decision-making process with analytical tools used across different levels in the organization as opposed to within specific groups. However, relying purely on AI systems for decision making could bring new risks. For this reason, manager should always ensure that the employees use also their critical thinking and experience along with the AI generated insights.

Trust and transparency are also mentioned as key issues. Employees have a lot of confidence in AI systems but not so much in how those systems work. This might be more relevant for multinationals particularly where there is much higher accountability and regulation. In practice, this might translate into organizations needing to pay more attention to the explainability and reviewability of AI decisions, and how clearly this is communicated to employees. A certain amount of human oversight can also help build trust over time. This could be extremely beneficial since organizations that invest at an early stage in explainability, and transparency may be more prepared for any future employee concerns or compliance obligations.

Finally, organizational support appears to be a key element in making AI adoption work in practice. Results indicate that when employees feel supported, for example through encouragement or access to resources, they are more likely to engage with AI tools. However, training appears to be a weak point. Employees may be asked to use AI, but they won't always have sufficient structured guidance on how to do so. This could limit their confidence and also affect how easy they find it to use such systems. This means that for multinational firms, support needs to be not just strategic, but also practical and consistent across different parts of the organization. Investments in training, communication, and employee development may generate benefits beyond technical competence by increasing trust, reducing uncertainty, and encouraging more effective use of AI tools across the organization.

5.4 Implications for Workforce Strategy & HR

The integration of AI into everyday work has obvious implications for workforce strategy and HR. A key takeaway from the findings is that AI is seen more as a job shifter than a job destroyer. Employees say there's more automation, but they're also taking on more complex tasks and responsibilities. This means that it is likely better for organizations to concentrate on adapting roles rather than reducing them. Organizations may achieve greater long-term outcomes by helping employees transition into new roles with more valued responsibilities rather than treating automation primarily as a cost-reduction mechanism.

From HR's perspective this points to job redesign. As some tasks get automated, roles don't remain the same, so they need to be adjusted. In practice, this means the addition of responsibilities related to analysis, oversight or decision support. But it's not always simple. If roles are not clearly redefined, employees may feel unsure of what is expected of them which can affect both performance and overall satisfaction. Moreover, unclear role definitions may increase resistance to organizational change and reduce employee engagement. For this reason, job redesign should be accompanied by clear communication regarding new responsibilities and expectations.

Another thing that comes through is the need to upskill. Even though organizations seem to support AI adoption in general, the findings suggest that training is not always strong enough. Because of that, HR strategies may need to place more emphasis on continuous learning, not just one-off training sessions. It may also be more effective to focus on practical, role-specific training rather than broad programs that are not directly connected to everyday tasks. The findings also suggest that upskilling should be viewed as a continuous process and not as a one-time action. AI systems constantly evolve and employees should be always prepared to remain effective and confidently use AI tools.

Employee perceptions are also important here. The results show that people can be positive about AI while still feeling some level of concern about job security. So, workforce strategies probably need to address both sides at the same time. Some of that uncertainty could be reduced by clear communication about why AI is being introduced and by involving employees in the process. When employees understand the purpose and expectations of AI initiatives, they may be more confident and willing to support such organizational changes.

Finally, HR may also need to spend more time building trust in AI systems. It is not just about teaching people how the systems work but also making sure they feel comfortable using them. Meanwhile, employees still need to use their own judgement particularly in more complex situations. So then it's more about balancing the use of AI with professional control over the decisions. This balance will be even more important as AI systems handling more complex tasks. Purely relying on AI could potentially reduce critical thinking and professional judgement, while excessive skepticism may limit the benefits that AI can provide. HR policies should therefore encourage employees to use AI as a supportive tool when it comes to decision making rather than a substitute for human expertise.

6 CONCLUSIONS & RECOMMENDATIONS

6.1 Summary of Research Contributions

Thus, the current study contributes to the existing literature on AI in organizations by examining the technology's impact from two perspectives simultaneously, i.e., operational efficiency and workforce dynamics. The research tries to associate both performance and employment related issues together in a single framework instead of addressing them separately. This was one of the motivations behind the study, as previous research often treats these areas separately, which may make it harder to fully understand how AI actually affects organizations in practice (Raisch & Krakowski, 2021).

Another important contribution is the use of evidence at the employee level. The study provides a more grounded picture of what AI adoption looks like in everyday work by considering how employees view AI in terms of its use, usefulness, trust, and impact on jobs. The results show that AI is no longer just a technical thing in the background but is already integrated into normal work processes. In this context, it is more apparent when observing daily routines than solely when looking at higher level organizational results.

The study also contributes to the discussion on workforce transformation. The findings suggest that AI is more likely to transform jobs than to eliminate them outright. Employees talk about more automation but at the same time they also talk about a shift towards more complex and higher value tasks. This is in line with task-based theories of technological change (Acemoglu & Restrepo, 2020). At the same time, the fact that people are worried about losing their jobs in the future suggests that the picture is not entirely simple. It appears that employees react not only to what they are experiencing now, but also to what they think could happen in the future.

There is contribution also in terms of technology acceptance. The findings validate the significance of perceived usefulness, which is in line with models like TAM (Venkatesh et al., 2012). But they also indicate that factors like trust and organizational support are key.

This indicates that in the context of AI, adoption is not only about the ease or utility of a system but also about the setting in which it is introduced and used.

The focus on multinational corporations adds another element to the study. Examining AI utilization in such organizations allows capturing more complex dynamics, such as the coordination across different units, the different levels of digital maturity and different employees' experiences. The results indicate that AI in these settings is not just a technological issue, but something that interacts with structure, management, and workforce diversity in a broader sense.

6.2 Practical Recommendations for Firms

The results of this study suggest several practical steps organizations can take to implement or scale AI. What is quite clear is that one of the main things is the need to incorporate AI into everyday work. AI is showing more value when embedded into everyday processes rather than being introduced as a separate initiative or in siloed pilot projects. That means making sure technology is really tied into the work people do every day. This is associated with higher chances that AI will be seen as useful and easier to put into practice.

Another issue, especially for multinational organizations, is the question of how a balance between standardization and flexibility can be found. The firms operate in very different environments. Therefore it would be always ideal to use the same solution everywhere. A more balanced approach could work better, with core systems and data structures centrally managed but at the same time allowing local teams to maintain some flexibility to adjust AI tools to their own needs. This will help to keep things consistent, but relevant to applications.

The findings suggest that from the perspective of workforce, organizations should pay more attention to job redesign than to job reduction. AI will take over the basic tasks, and jobs will evolve naturally. In practice this often means a greater emphasis on analytical work, supervision or support of decision making. But the transition has to be done carefully. If employees don't know how their jobs are changing, uncertainty can creep in pretty fast. For this reason, clear communication at this stage is crucial.

Another thing that stands out is re-skilling. But many organizations that appear to be adopting AI are at different levels of training. This means that companies may need to incur more costs on continuous education than on one-time training. Training is also more valuable when it is specific to certain roles so employees can apply what they learn to their day to day work.

Trust and transparency are also worth paying attention to. Employees say they trust AI systems, but they don't always understand how those systems work. This can provide some uncertainty in the background. This means organizations might have to go the extra mile to explain how AI decisions are made and ensure there are processes in place to review or challenge outputs when needed. Retaining some level of human interaction can also help maintain confidence.

At the same time, it is also important to consider employees' feelings towards AI. The results suggest that although people may have a rosy view of the benefits they are nevertheless concerned about job security. Concerns do not always translate into behavioral resistance but should not be ignored. Open discussion of what AI is supposed to do and what it is supposed to achieve can help here, as can more employee involvement in the implementation process.

And at the end of the day, companies need to do more than throw out generic encouragement. It has to be there in practice, in the access to tools, the training and support. Without this kind of consistent support, employees may not be able to fully benefit from AI even when the technology is there.

In conclusion, these points suggest that the successful adoption of AI is not merely about spending money on technology itself. It also depends on how well organizations align their processes, prepare their workforce and "choreograph" the entire employee journey.

6.3 Policy & Ethical Recommendations

The findings of the study also show the importance and the necessity of implementing proper governance frameworks when it comes to AI. The correct implementation of AI technologies is not always sufficient without taking into account its ethical and organizational implications that it can cause. As the involvement of the AI in decision-making and everyday processes increases more and more, issues like transparency, accountability, and data protection start to matter more. For example, based on the results, employees argued that they do not always fully understand how AI systems produce their outputs, even if they still trust and use them. This makes it obvious that the establishment of clearer policies around explainability and how AI-based decisions are made is even more essential.

One thing that could help with the situation described is that organizations may need to set more detailed guidelines around AI use. Some examples could be proper documentation of how decisions are generated, the existence of accurate audit processes, and the clear communication of who is responsible for what. Human oversight should remain strong at some points, especially in situations where AI is used for more sensitive or high-impact decisions. In practice, this “human-in-the-loop” approach can help maintain accountability while still allowing AI to support decision-making.

Data privacy is another area that cannot be ignored. Since AI systems depend on large amounts of data processing, organizations need to ensure that they are following regulatory requirements so that they can protect both employee and customer sensitive information. At the same time, being clear about how data is collected and used can also help build trust among employees, an aspect that seems quite important based on the findings.

Additionally, there is a dilemma when it comes to fairness and bias. It seems like eventually organizations will be forced to always monitor AI systems and check whether there are unintended biases in how decisions are formed. This is something that from the looks of it, it will be here to stay, and it won’t be something that can be handled once and then forgotten. Monitoring will also be required to ensure outcomes stay aligned regarding ethical standards and legal expectations. At this point, we could say that ethical AI is not just a technical issue but more of an ongoing responsibility.

6.4 Limitations of the Study

Like most studies, this study has some limitations which should be borne in mind while interpreting the results.

A first point concerns the research design. The study is a cross-sectional survey. Therefore, it only reflects perception at a single point in time. This makes it difficult to see how attitudes could shift as AI becomes more embedded in organizations. In fact, their views could shift as employees gain more experience with AI or as systems become more sophisticated, but that is not captured here.

Another limitation is the use of self-reported data. It's not about the performance of the employees, or the objective results, it's about how they perceive AI. This is a good way of understanding everyday experience, but the responses could be colored by personal opinions, different interpretations or just how familiar people are with AI tools.

The sampling approach also needs to be considered. The use of convenience and snowball sampling assisted in the collection of responses, but it does mean that the sample is not fully representative. So the findings may not be applicable in exactly the same way to all organizations or groups of employees.

It's also worth noting that the study doesn't delve into the details of any specific industry or company. The analysis is done in a general way despite the sample consisting of participants from different sectors. This makes it more challenging to find patterns specific to the industry.

Finally, the main attention is directed to the views of the employees. It does provide useful insight but is missing managerial or organizational level data that could have added another layer to the analysis. Including these perspectives may help future research to provide a fuller picture of how AI is adopted in practice.

6.5 Suggestions for Future Research

Maybe there are a few ways future research could take this study a little further. One thing you could do is look at how things change over time. This study is cross-sectional so it does not really show how opinions can change. It's possible that people see AI differently once they get used to it, but that's not something we can really see here.

Another thing that comes to mind is the difference between perception and reality. The majority of results here are based on employees' perceptions of productivity or efficiency. But it isn't always like that, as it might be clearer from perceptions and actual performance. At this moment, the focus is on employees. Managers or senior staff may see things from a different perspective, particularly with regard to decisions or strategy. Incorporating those views may account for some of the gaps that appear.

Another aspect to consider is the context. Different industries or even different regions might take very different approaches to AI. This study doesn't really go into that detail. Comparing contexts might reveal things that are not apparent here.

Leadership and culture are other areas that feel a little underexplored. The findings suggest that support matters, but how it works in practice is not so important. It would be interesting to see what kind of environment is easier for AI to accept.

And finally, ethics is probably going to become more important, not less important. things like transparency or data privacy are already there but they are likely to be bigger issues Future studies might investigate more closely how organizations deal with these issues in day-to-day situations.

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Appendix A: Questionnaire

Participant Information & Consent Form

You are invited to participate in a research study conducted as part of a Master's Dissertation in the MBA Programme of the Hellenic Open University (HOU).

The purpose of this study is to examine the integration of Artificial Intelligence (AI) in multinational corporations, with a particular focus on its impact on operational efficiency and workforce dynamics. The research aims to explore how AI technologies are used in organizational processes and how employees perceive their influence on work practices, productivity, and job roles.

Your participation in this study is entirely voluntary. You may choose not to participate or to withdraw at any time without any consequences.

The questionnaire is anonymous, and no personally identifiable information will be collected. All responses will be treated with strict confidentiality and will be used exclusively for academic purposes. The data collected will be analyzed in aggregated form and won't be used to identify individual participants or organizations.

The survey is expected to take approximately 5–7 minutes to complete.

By proceeding with this questionnaire, you confirm that:

- ✓ You have read and understood the information provided above
- ✓ You voluntarily agree to participate in this study
- ✓ You are at least 18 years old

If you have any questions regarding the study, you may contact the researcher via email.

Thank you for your time and contribution.

Section A – Demographics

Age:

18–25 / 26–35 / 36–45 / 46+

Gender:

Male / Female / Prefer not to say

Department:

Finance / HR / IT / Operations / Customer Service / Other

Years of experience:

<2 / 2–5 / 6–10 / 10+

Company type:

Telecommunications / Pharma / Finance / Other

Section B – AI Usage in the Workplace

Likert Scale (1–5): Strongly Disagree → Strongly Agree

AI tools are integrated into my daily work tasks

I frequently use AI-based systems in my job

AI is used in key processes within my department

My organization actively promotes the use of AI technologies

Section C – Perceived Usefulness & Ease of Use (TAM)

Perceived Usefulness

AI improves my job performance

AI increases my productivity

AI helps me accomplish tasks more quickly

Ease of Use

AI tools are easy to use

Learning to use AI systems is easy for me

Interaction with AI systems is clear and understandable

Section D – Operational Efficiency

AI reduces the time required to complete tasks

AI improves process accuracy and reduces errors

AI enhances decision-making in my role

AI contributes to better overall organizational performance

Section E – Workforce Impact

AI has changed the nature of my job

Some tasks I used to perform are now automated

AI allows me to focus on more complex tasks

AI may reduce the need for certain roles in the future

Section F – Trust in AI

I trust the outputs generated by AI systems

AI systems in my organization are reliable

AI decisions are transparent and understandable

I feel comfortable relying on AI for work-related decisions

Section G – Fear & Resistance

I am concerned that AI could replace my job

AI makes me feel uncertain about my future role

I prefer to rely on human judgment over AI

I am hesitant to fully adopt AI tools

Section H – Organizational Support

My organization provides adequate training on AI tools

Management supports the use of AI technologies

I feel supported when using AI systems

My organization encourages digital upskilling

Author's Statement:

I hereby expressly declare that, according to the article 8 of Law 1559/1986, this dissertation is solely the product of my personal work, does not infringe any intellectual property, personality and personal data rights of third parties, does not contain works/contributions from third parties for which the permission of the authors/beneficiaries is required, is not the product of partial or total plagiarism, and that the sources used are limited to the literature references alone and meet the rules of scientific citations.