ΠΟΛΥΤΕΧΝΕΙΟ ΚΡΗΤΗΣ
TECHNICAL UNIVERSITY OF CRETE

MASTER IN TECHNOLOGY & INNOVATION MANAGEMENT

Thesis, 12/07/2025

Impact of automation and artificial intelligence on the future of work: a strategic perspective

Supervisor: Dr. Moustakis Vasileios

Student : Kali Sofia | **ID**: 2021015008

Table of Contents

INTRODUCTION

The Fourth Industrial Revolution is not just reshaping industries; it's redefining what it means to work and contribute to a digital age. Recent academic and industry developments confirm that AI and automation have become central to global transformation, influencing both daily work and long-term strategic operations (Shin, 2020).

Once limited to futuristic speculation, AI now permeates daily life. Technologies like autonomous vehicles and natural language processing have moved from labs to highways and smartphones. Tesla's self-driving capabilities and GPT-powered chatbots from OpenAI are prime examples that I've seen repeatedly cited in both academic and mainstream discussions (Tesla; OpenAI, 2023). These tools aren't just innovations-they're redefining interaction and efficiency in real time.

Our increasing reliance on smart systems, from Alexa to Siri, signals a deeper integration of AI and IoT into everyday decision-making (Shin, 2020). In both personal and business environments, these technologies are transitioning from supportive tools to decision-makers themselves. That shift is both exciting and unnerving.

In the business realm, AI is praised for its ability to boost productivity and cut costs. However, I can't help but reflect on the questions it raises-especially regarding job displacement and the ethical implications of letting algorithms make human-centric decisions. This duality between progress and disruption lies at the heart of my inquiry.

AI and related technologies are undoubtedly "disruptive", as many scholars assert. However, unlike earlier transformative inventions such as the steam engine or the printing press, today's innovations introduce not only economic shifts but also deep psychological, ethical, and existential challenges. The disruption is no longer limited to how we work but extends to how we define ourselves in relation to intelligent machines (Floridi et al., 2018; Bostrom, 2014).

Throughout this thesis, I aim to examine how automation and AI are transforming the workforce, with a strategic focus on the skills, structures, and ethics we need to adapt. My goal is not only to understand these shifts but to offer thoughtful recommendations-especially around reskilling, human resource strategies, and equitable adoption of technology.

Objectives

1. To assess the strategic implications of automation and AI on business operations and workforce structures across various industries.

2. To explore the role of AI in human resource management, including talent acquisition, employee training, and performance evaluations, with a focus on AI's potential to enhance productivity and sustainability.

3. To evaluate the ethical and social impacts of AI and automation on job security, skills development, workforce inequalities, and the regulatory frameworks required to address these challenges.

4. To examine how organizations can integrate AI and automation into their operations strategically, ensuring alignment with business objectives and competitive advantage.

5. To identify key factors driving AI adoption in the workforce, considering technological, economic, and social influences that shape organizational behavior and labor market dynamics.

6. To provide recommendations for policymakers and business leaders on addressing the risks and opportunities posed by AI and automation, while promoting ethical and sustainable practices in the workplace.

Research questions / goals

1. Are there significant differences in employees' willingness to participate in reskilling/upskilling programs based on industry and work experience?
2. To what extent do perceive job security, perceived impact of AI on job tasks, and trust in management predict employee attitudes towards AI and automation?
3. What is the degree of impact of automation and artificial intelligence on human resources, consumers and the future of work in companies?
4. How does automation and AI influence the need for reskilling and upskilling among employees?

Dissertation Structure

This dissertation is organized into four core chapters, followed by references and appendices. Each chapter is structured to progressively build the theoretical foundation, outline the methodological approach, analyze the empirical data, and synthesize conclusions relevant to the strategic impact of automation and artificial intelligence (AI) on the future of work.

Chapter 1: Literature Review

This chapter presents a comprehensive review of the academic literature and theoretical frameworks underpinning the study. It begins by examining the evolution and classification of AI and automation technologies and explores their application across strategic business functions. It further addresses labor market transformations, ethical and regulatory challenges, and sector-specific impacts of technological adoption. The review culminates with a discussion of the strategic imperatives for organizations navigating the AI-driven future of work.

Chapter 2: Research Methodology

This chapter outlines the philosophical and methodological foundations of the research. It details the study's positivist paradigm, quantitative approach, and cross-sectional, explanatory design. The chapter also presents the process of questionnaire development and pretesting, describes the data collection procedures, elaborates on sampling strategies, and explains the statistical methods used for data analysis. Reliability and validity assessments, as well as ethical considerations, are also addressed comprehensively.

Chapter 3: Results and Findings

This chapter presents the empirical results derived from the quantitative data. It begins with a demographic profile of the respondents and then presents findings across five thematic dimensions: AI and automation in security and ethics, organizational sustainability, social and ethical impacts, strategic integration, and implications for human resources and the future of work. Data are analyzed using descriptive and inferential statistics, and the results are interpreted in relation to the research objectives.

Chapter 4: Summary and Conclusion

The final chapter summarizes the main conclusions of the study and discusses their managerial, theoretical, and policy implications. It also reflects on the limitations of the research and proposes directions for future studies, particularly in the context of strategic workforce planning and AI implementation.

The dissertation concludes with a bibliographic reference list and an appendix section, which includes the full research questionnaire and its thematic sections.

Keywords: Automation, Artificial Intelligence, Future of Work, Strategic Management, Ethics, Human Resources, Economic Development, Reskilling, Upskilling

Acronyms

a) Technical and Strategic Acronyms

AI	Artificial Intelligence
RPA	Robotic Process Automation
DSM	Decision Support Mechanisms
ERP	Enterprise Resource Planning
CRM	Customer Relationship Management
SPSS	Statistical Package for the Social Sciences
IoT	Internet of Things
NLP	Natural Language Processing
ML	Machine Learning
GOFAI	Good Old-Fashioned Artificial Intelligence
ANI	Artificial Narrow Intelligence
AGI	Artificial General Intelligence

ASI	Artificial Superintelligence

b) Statistical and Research Acronyms

HR	Human Resources
EBDM	Evidence-Based Decision-Making
DEI	Diversity, Equity, and Inclusion
ANOVA	Analysis of Variance
df	Degrees of Freedom
α (alpha)	Significance Level (typically set at 0.05)
N	Number of Participants (sample size)

c) Organizations and Frameworks

OECD	Organisation for Economic Co-operation and Development
GDPR	General Data Protection Regulation
WEF	World Economic Forum
EU	European Union

CHAPTER 1: LITERATURE REVIEW

AI and automation have come a long way since they were just simple mechanical tools and software that followed rules. Now, they are complex systems that can learn, change, and help people make tough decisions. These technologies are no longer just for making things more efficient; they are now a key part of how businesses respond to changes in the market, manage their people, and reach their strategic goals (Brynjolfsson & McAfee, 2014; Chui et al., 2018).

Robotic Process Automation (RPA) and AI are becoming more common in many fields, including HR, finance, logistics, and customer service. This means that we need to rethink how we work. RPA takes care of repetitive tasks like payroll and data entry, which gives employees more time. AI technologies, on the other hand, look for patterns in big datasets to help with forecasting, risk management, and resource planning (Lacity & Willcocks, 2015; Rajesh et al., 2018; Gunderson et al., 2024).

These capabilities are rapidly entering domains like healthcare and education, where AI is not just optimizing back-end systems but influencing how critical decisions are made. This shift has prompted growing scrutiny over how these tools are designed and deployed, especially when it comes to fairness, transparency, and accountability (Crawford, 2021; Mittelstadt, 2019). Algorithms used in hiring, for example, can reinforce existing biases if not carefully monitored (Dastin, 2018; Raghavan et al., 2020).

To navigate this landscape, organizations must think beyond technology investment. Successful AI integration depends on employee engagement, leadership readiness, and clear ethical frameworks. Companies like IBM and Accenture are leading by example, coupling digital tools with in-house training platforms that promote inclusive learning and reskilling (IBM, 2023; Accenture, 2022).

Decision Support Mechanisms (DSM) powered by AI are becoming strategic tools, guiding everything from workforce planning to performance evaluation. But these systems work best when they support-rather than substitute-human judgment, ensuring ethical oversight and organizational agility (Davenport & Ronanki, 2018; Shollo & Galliers, 2016; Raisch & Krakowski, 2020).

As AI adoption accelerates, so do concerns over job displacement, equity, and control over decision-making processes (Fu & Mishra, 2021; Benanav, 2019). Addressing these concerns requires inclusive policies and leadership that values diverse perspectives, principles that many forward-looking companies are beginning to embrace (World Economic Forum, 2023).

This chapter reviews the current academic and industry literature on AI and automation, focusing on their technological foundations, workplace impact, ethical challenges, and the practical realities of organizational transformation. It also highlights gaps in the research-particularly the need for more data on how companies are managing the human side of this technological shift.

1.1 Technological Foundations and Classifications

1.1.1 Evolution and Definition of AI and Automation

The foundations of artificial intelligence trace back to Alan Turing's seminal paper, where he posed the question of whether machines could mimic human thought-a concept now known as the Turing Test (Turing, 1950). For decades, AI research focused on symbolic logic and rule-based systems, often described as "Good Old-Fashioned AI" or GOFAI (Russell & Norvig, 2020). In recent decades, however, AI has undergone a shift toward probabilistic models and data-driven learning, enabled by the explosion of data and computational power.

Modern definitions of AI vary. The European Parliament (2018) characterizes AI as systems-either software-based or embedded in hardware-that exhibit autonomy in learning, decision-making, and reasoning. Other scholars suggest that AI is a constantly evolving concept, shaped by advances in technology and shifting societal expectations (Sartori & Theodorou, 2022).

Automation, by contrast, refers to systems, digital or mechanical, that perform predefined tasks with minimal human input. It is used in a wide array of contexts, from manufacturing lines to backend software, to improve accuracy, reduce costs, and enhance speed (Willcocks, Lacity, & Craig, 2015).

For organizations, these technologies offer more than operational advantages-they provide strategic capabilities. But effective integration requires a parallel investment in skills development, organizational restructuring, and ethical governance.

1.1.2 Types of AI and Robotic Process Automation (RPA)

AI is generally divided into three conceptual categories. Artificial superintelligence (ASI) refers to a theoretical form of AI that would surpass human cognitive abilities in every aspect. This advanced software-based intelligence would possess superior reasoning, problem-solving, and learning capabilities far beyond the human mind.

Although ASI remains a concept of the future, many current technologies lay the groundwork for its development. However, to understand how distant ASI still is, it's important to recognize that today's AI is primarily classified as Artificial Narrow Intelligence (ANI), also known as weak or narrow AI.

Weak AI is highly effective at performing specific tasks-such as language translation or chess-but lacks the capacity to generalize knowledge or autonomously acquire new skills. It operates based on predefined algorithms and data sets, often requiring human guidance to function properly.

There is ongoing debate among experts regarding whether ASI is achievable at all. Human intelligence itself is shaped by unique evolutionary pressures and might not represent a universal model of intelligence. Additionally, because the human brain remains only partially understood, replicating its complexity through machines remains a significant scientific and technological challenge. (Mucci & Stryker, 2023).

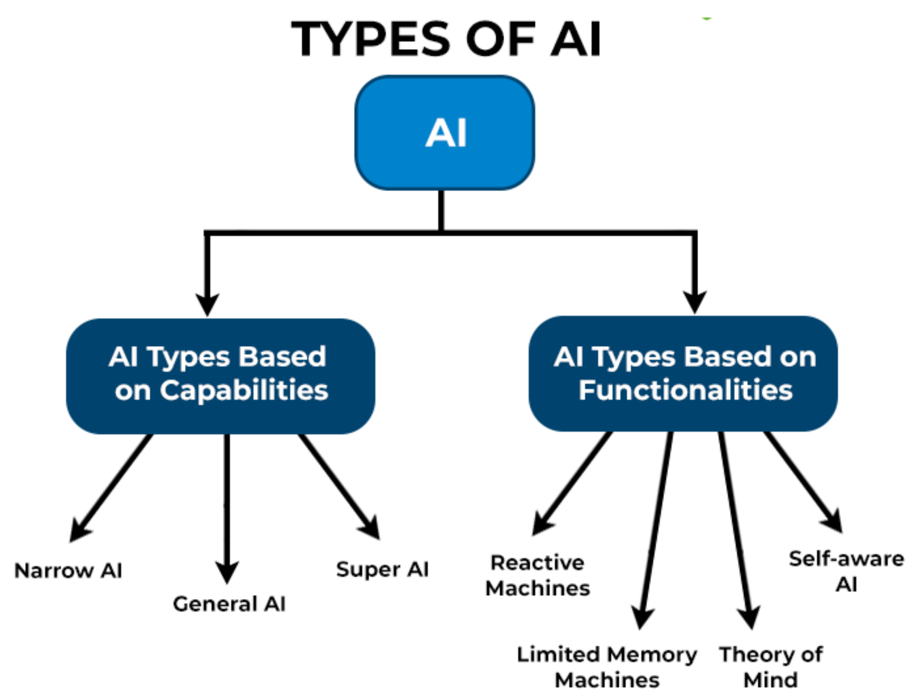

Figure 1, Source: https://www.spiceworks.com/tech/artificial-intelligence/articles/types-of-ai/

Despite their limitations, ANI systems drive significant value. For instance, Amazon’s and Netflix’s recommendation engines use behavioral data to personalize user experiences and increase engagement (Gómez-Uribe & Hunt, 2015).

Robotic Process Automation (RPA) differs in that it doesn’t involve learning or cognition. Instead, RPA automates rule-based, repetitive digital tasks like data entry or payroll processing, increasing efficiency and accuracy in administrative operations (Lacity & Willcocks, 2015; Siderska, 2020).

The term “robot” was first introduced in a 1921 play by Czech writer Karel Čapek. However, in today’s context, RPA "robots" are not physical machines but software tools that replicate human actions on digital systems (Tarus et al., 2018). Their success hinges on effective system integration, ongoing monitoring, and alignment with business processes (Siderska, 2020).

According to UNESCO, modern robots are artificial entities with essential traits such as mobility, interactivity, communication, and autonomy, enabling them to function effectively in human-centered environments like hospitals or offices (Holstein et al., 2019). These capabilities are achieved through sensor systems, actuators, and speech recognition technologies, all coordinated by embedded AI.

Contrary to popular imagery, Robotic Process Automation (RPA) does not involve physical robots but refers to software solutions that automate routine tasks previously performed by humans. Common uses include data entry, document processing, and updating databases across systems such as ERP or CRM platforms (Lacity et al., 2015). It is important to note that mimicking human actions requires a minimum level of integration with existing information systems. Acting as a virtual workforce, RPA is tasked with automating manual and repetitive activities. However, to achieve successful automation, it is necessary to possess knowledge of automation capabilities, improve robots, and continuously monitor processes to implement necessary adjustments (Helm et al, 2020).

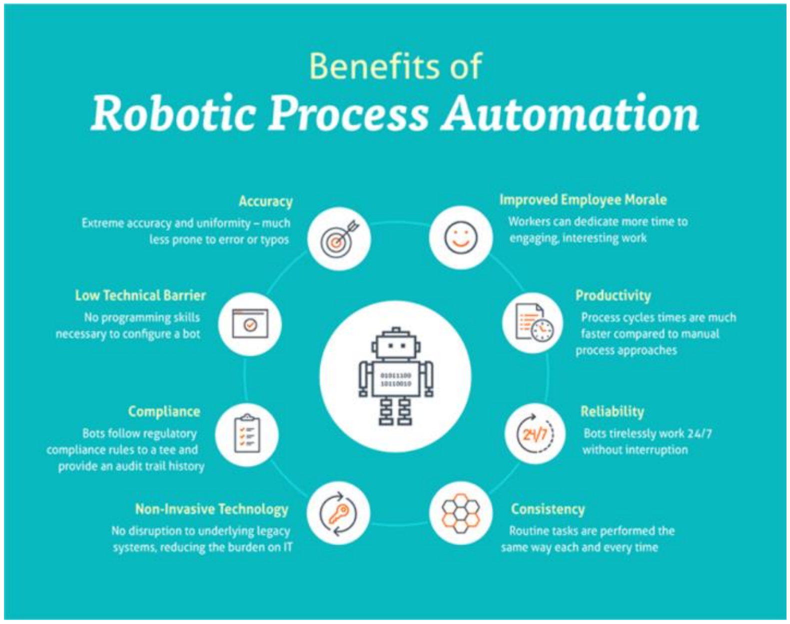

Figure 2, Source: Laserfiche. https://www.laserfiche.com/ecmblog/what-is-robotic-process-automation-rpa/

Businesses adopting AI and RPA must also recognize their implications for workforce design. The strategic deployment of these tools often entails restructuring job roles, redefining skill requirements, and building DSM systems that integrate human and machine inputs (Raisch & Krakowski, 2020). Many organizations have responded with upskilling programs to reskill workers whose roles are disrupted by automation. For instance, Amazon's $1.2 billion "Upskilling 2025" initiative trains employees for roles in data analysis, cloud computing, and machine learning (Amazon, 2021).

Importantly, AI and RPA implementations must be aligned with diversity, equity, and inclusion (DEI) principles to avoid creating digital divides. When properly designed, these systems can support more equitable access to opportunity-especially if reskilling programs prioritize underrepresented or historically marginalized groups (World Economic Forum, 2023).

1.1.3 Human–Machine Collaboration and Autonomy

The current phase of intelligent automation is characterized by adaptive human machine collaboration, where AI enhances but does not fully replace human capabilities. This hybrid model is exemplified in sectors such as logistics, medicine, and education. For instance, in healthcare, AI tools assist radiologists in detecting anomalies more accurately and rapidly, yet final diagnoses remain under clinician oversight (Yildirim et al., 2024).

Autonomy in intelligent systems is enabled by stochastic algorithms, which can learn from data and adjust behavior based on environmental feedback rather than fixed rule sets (Goswami & Mondal, 2025). This capability allows robots and AI agents to navigate unstructured or dynamic environments, such as self-driving cars operating on city streets (Bathla et al., 2022), or warehouse robots adapting to shifting inventory demands.

The strategic implications for business are profound. Autonomous systems can reduce reliance on manual oversight, improve response times, and increase system resilience-particularly during crises or labor shortages. But autonomy also demands robust oversight frameworks to manage risks related to safety, liability, and ethical accountability (Crawford, 2021).

To support these changes, businesses must invest in decision support infrastructure, ensuring that AI outputs are transparent, interpretable, and contextually valid. Organizational leaders must also build trust with employees, especially in scenarios where decisions affecting job assignments, compensation, or promotion are partially AI-mediated (Binns, 2018). Strategic success thus hinges not only on algorithmic performance but also on institutional trust, inclusivity, and human-centered implementation.

1.2 Strategic Integration in Organizational Functions and the Need for Reskilling

The integration of artificial intelligence (AI) and automation into organizational operations is not merely a technological shift but a strategic transformation that redefines how businesses create value, make decisions, and engage their workforce. As these technologies move beyond siloed applications into core business processes-particularly in human resources, finance, operations, and customer engagement-firms are compelled to adapt by restructuring workflows, investing in reskilling, and rethinking strategic human machine collaboration (Davenport et al., 2020).

1.2.1 Strategic AI Adoption in Core Business Functions

Artificial intelligence (AI) is no longer a peripheral innovation; it now plays a central role in enhancing accuracy, speed, and strategic decision-making across core business functions. In operations, AI-driven predictive maintenance systems anticipate equipment failures, enabling companies to reduce downtime and control costs (Lee, Bagheri, & Kao, 2014). Similarly, supply chain optimization has become increasingly data-driven, with AI models helping firms forecast demand and manage inventory with greater agility (Choi, Wallace, & Wang, 2021).

In the financial sector, AI applications range from fraud detection to compliance automation and algorithmic trading, driving operational efficiencies and competitive advantages (Lam, 2025). Meanwhile, customer service and marketing functions benefit from AI-powered personalization, increasing customer engagement and lifetime value (Gómez-Uribe & Hunt, 2015).

Enterprise software platforms like SAP's Business Technology Platform and Salesforce's Einstein embed AI into enterprise resource planning (ERP) and customer relationship management (CRM) tools, enabling executives to base strategic decisions on predictive analytics and cross-functional data (Raisch & Krakowski, 2020).

However, integrating AI successfully often requires organizational change. Companies that restructure workflows, flatten decision hierarchies, and reskill employees tend to report better returns on their AI investments (Manyika et al., 2017).

1.2.2 Human Resources and the Workforce Transformation Imperative

The human resources (HR) function plays a pivotal role in orchestrating this transformation. AI-enabled tools now manage tasks ranging from résumé screening and candidate matching to performance monitoring and career pathing (Tambe et al., 2019). These applications improve efficiency, reduce bias in selection, and offer predictive insights into employee turnover or engagement (Ghedabna et al., 2024).

However, such automation raises critical challenges in workforce dynamics. As AI and RPA reduce the need for certain manual or administrative tasks, firms face the dual imperative of managing job displacement risk and building a future-ready workforce. The World Economic Forum (2023) estimates that 44% of workers' skills will be disrupted by 2027, and over 75% of companies plan to adopt AI-driven tools-making reskilling a strategic necessity.

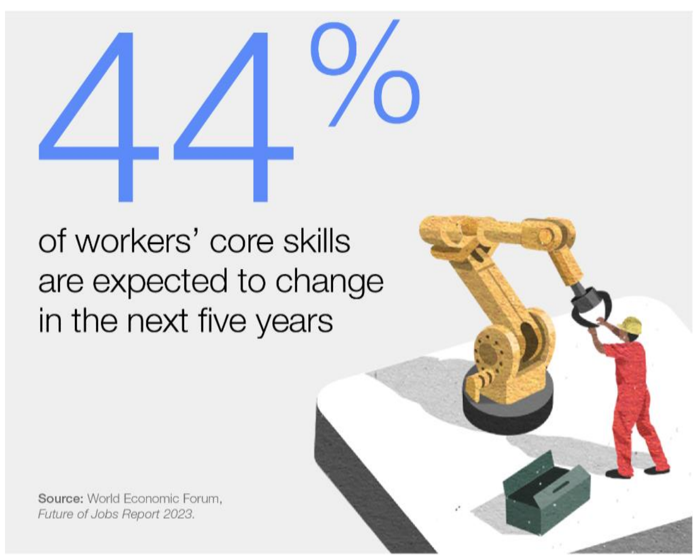

Figure 3, Source: World Economic Forum.
https://www.weforum.org/stories/2023/05/future-of-jobs-2023-skills

Educational institutions and private organizations must collaborate to redesign curricula and create personalized, continuous learning pathways. A future-ready workforce will require a hybrid of digital, cognitive, and interpersonal competencies

Companies like IBM and Accenture have already developed in-house training academies to close AI skills gaps, focusing on areas such as data literacy, ethical AI, digital collaboration, and strategic thinking (IBM, 2021; Accenture, 2023). These initiatives are not merely HR functions-they are strategic investments that influence competitive advantage and employee retention.

Additionally, reskilling initiatives must be inclusive. Ensuring diversity, equity, and inclusion (DEI) in upskilling programs mitigates the risk of exacerbating digital divides. Organizations that prioritize DEI in tech adoption-such as GSI by Microsoft with Linkedin and GitHub "Global Skills Initiative" targeting underserved communities-demonstrate that AI can be a tool for empowerment, not exclusion (Microsoft, 2022).

1.2.3 Motivating and Engaging Employees During Digital Transformation

Digital transformation, when not accompanied by strategic communication and cultural readiness, may lead to employee resistance, anxiety, or disengagement (Bughin et al., 2018). Employees must be motivated to adopt new tools, trust AI-enabled systems, and understand the strategic value of human–machine collaboration. This requires:

- Transparent communication about the role of AI and its impact on roles and workflows.
- Employee involvement in AI pilot testing and system evaluation.
- Recognition and rewards for digital adaptability and innovation.

- Integration of human-centric design principles that preserve autonomy and dignity in work (Westerman et al., 2014).

Leadership also plays a crucial role in modeling AI adoption. Research shows that transformational leadership behaviors-such as coaching, vision setting, and individualized consideration-improve acceptance of AI tools among employees (Divya et al., 2024). The strategic alignment of technological and human capital initiatives thus becomes a key success factor.

1.2.4 AI, Strategic Agility, and Organizational Learning

AI’s true value is realized not through isolated deployments but through systemic integration that enables continuous learning, rapid feedback loops, and real-time strategy adjustment. AI-enhanced DSM frameworks give businesses the agility to respond to market shifts, competitor moves, and regulatory changes faster than traditional hierarchies allow (Davenport & Ronanki, 2018).

To institutionalize such agility, firms must embrace a culture of lifelong learning. This means formalizing internal learning ecosystems-such as AI learning labs, micro-certification programs, or interdepartmental innovation hubs-that foster experimentation and bridge the gap between technical and strategic teams.

In sum, AI and automation offer not just cost efficiencies but strategic capabilities that can transform core business functions, workforce planning, and long-term competitiveness. However, their successful integration depends on an aligned strategy that emphasizes employee development, inclusive reskilling, participatory leadership, and ethical deployment. Organizations that manage this transformation holistically balancing technology and people are more likely to thrive in the AI-enabled economy.

1.3 Labor Market Dynamics: Job Displacement, Skill Shifts, and Workforce Adaptation

The integration of artificial intelligence (AI) and automation is fundamentally reshaping labor markets around the world. These technologies drive productivity gains and economic growth while simultaneously generating complex challenges for workforce sustainability, job security, and socio-economic inclusion. The shift from task-based to skill-based work raises critical concerns about displacement, reskilling, and strategic adaptation across both public and private sectors (Acemoglu & Restrepo, 2018; World Economic Forum, 2023).

1.3.1 Automation-Driven Job Displacement and Transformation

While past industrial revolutions primarily displaced manual labor, today's AI-driven wave impacts both low and high-skilled jobs, including administrative, legal, healthcare, and finance roles (Arntz et al., 2016). According to the McKinsey Global Institute, AI and automation could potentially displace between 400 and 800 million jobs globally by 2030, particularly in sectors reliant on routine tasks (Manyika et al., 2017).

However, displacement does not equate to mass unemployment. Historically, technology has also created new roles, often in adjacent or emerging sectors. In AI's case, this includes roles in data science, machine learning, AI ethics, digital product management, and new forms of customer interaction (Bessen, 2019).

1.3.2 Evolving Skill Demands and the Strategic Reskilling Imperative

The strategic shift is not from "jobs lost" to "jobs gained," but from tasks automated to skills demanded. Employers now value complex cognitive skills-such as critical thinking, problem solving, and decision-making alongside digital fluency and adaptive learning capacity (Brynjolfsson & McAfee, 2014). According to the World Economic Forum (2023), the top in-demand skills include analytical thinking, self-management, resilience, and the ability to work with AI systems.

Firms that fail to upskill or reskill their workforce risk creating internal labor mismatches, reducing both productivity and employee satisfaction. This strategic alignment requires not only training programs, but a redefinition of workforce planning, talent acquisition, and job design to focus on capability portfolios rather than static roles (Deloitte, 2023).

To support this, companies such as Siemens, Unilever, and PwC have launched corporate learning academies, while IBM's SkillsBuild platform provides digital learning for both internal staff and underserved external communities (IBM, 2021). Such initiatives link reskilling to business strategy, helping companies remain competitive while fulfilling social responsibility mandates.

1.3.3 Motivation, Equity, and Inclusion in Workforce Adaptation

Adoption of AI and automation must account for employee motivation and psychological readiness. Without employee buy-in, digital transformation efforts are likely to fail or stagnate (Bughin et al., 2018). Leaders must cultivate growth mindsets through open communication, participatory system rollouts, and recognition of upskilling achievements (Nguyen et al., 2023). Employees must be empowered as change agents, not passive recipients of technological shifts.

Crucially, reskilling strategies must be inclusive. Automation disproportionately threatens roles held by women, older workers, and historically marginalized populations-particularly in administrative and customer service occupations (Carbonero et al., 2020). To mitigate inequality, businesses must embed Diversity, Equity, and

Inclusion (DEI) principles into reskilling programs, ensuring equal access to training, digital tools, and mentoring opportunities.

For instance, AT&T's "Future Ready" initiative targets workforce equity by investing in DEI-sensitive retraining across all career levels. Meanwhile, Salesforce’s Trailhead program democratizes digital upskilling via open-access training on CRM, analytics, and AI literacy (Salesforce, 2022).

1.3.4 Public–Private Partnerships and Policy Considerations

Governments also play a pivotal role in facilitating labor market resilience. Strategic policy tools such as tax incentives for corporate training, wage subsidies during retraining, and public AI education programs can accelerate adaptation. For example, Singapore’s “SkillsFuture” framework offers credits for lifelong learning and collaborates with employers to forecast emerging skill needs (Skills Future Singapore, n.d.).

Furthermore, policy frameworks must support ethical workforce transitions, including protections against precarious employment and algorithmic bias in hiring and evaluation (Raghavan et al., 2020). Labor law reform is increasingly needed to address issues like job classification in platform work, digital surveillance, and accountability in AI-based decision-making systems (West et al., 2019).

1.3.5 Strategic Decision-Making and Workforce Planning

AI integration reshapes not only operations but also strategic workforce planning. Decision-making tools such as predictive workforce analytics and AI-assisted scenario modeling now allow HR and executive teams to anticipate skill gaps, optimize team composition, and align human capital strategy with technological innovation (Tambe et al., 2019).

This represents a shift toward evidence-based decision-making (EBDM) in HR, where AI insights inform reskilling investments, internal mobility plans, and diversity goals. Firms must therefore build cross-functional teams-linking data science, HR, and operations-to guide adaptive talent strategies with both business performance and social equity in mind.

The future of work under AI and automation is not predetermined but contingent on the strategic responses of organizations and policymakers. Companies that proactively invest in inclusive reskilling, human-centric change management, and data-informed workforce planning are better positioned to maintain competitiveness, employee engagement, and long-term resilience. Rather than replace human labor, AI has the potential to augment human capabilities-provided that businesses frame its adoption not just as a technical upgrade, but as a strategic, ethical, and inclusive transformation.

1.4 Ethical and Regulatory Considerations in AI and Automation

The rapid diffusion of artificial intelligence (AI) and automation technologies has brought not only operational efficiencies and strategic advantages, but also profound ethical and regulatory challenges. As these systems increasingly mediate decisions in employment, healthcare, finance, and governance, they raise complex questions regarding fairness, accountability, transparency, and human dignity (Binns, 2018; Mittelstadt et al., 2016).

Organizations aiming to integrate AI into strategic decision-making must therefore adopt a multi-level ethics strategy-one that aligns technological innovation with internal values, regulatory frameworks, and societal expectations.

1.4.1 Algorithmic Bias and Decision-Making Integrity

AI systems often rely on historical or proxy data to inform predictive models. When historical data reflects systemic inequalities, AI systems may unintentionally perpetuate or amplify these biases in decision-making processes (Barocas & Selbst, 2016).

In strategic HR decision-making, for example, AI systems trained on biased résumé data may disadvantage women, racial minorities, or candidates with non-traditional educational backgrounds (Raghavan et al., 2020). Thus, ensuring algorithmic fairness and explainability is not only a technical imperative but a core governance priority for any data-driven enterprise.

Large firms such as Google and Microsoft have developed AI ethics boards and bias testing protocols to assess the fairness of algorithms before deployment. However, critics argue that internal mechanisms may lack enforceability or transparency, underscoring the need for independent oversight and external accountability standards (Whittlestone et al., 2019).

1.4.2 Privacy, Surveillance, and Data Sovereignty

The success of AI models depends on vast datasets-often including personal, behavioral, and biometric information. While such data enables hyper-personalization and predictive analytics, it also amplifies surveillance risks and raises concerns about data ownership and consent (Zuboff, 2019).

In workplace environments, AI is increasingly used to monitor employee activities, assess productivity, predict turnover risk raising ethical concerns around surveillance and autonomy (Ball, 2010).

Firms must therefore embed data governance principles into their strategic architecture, ensuring GDPR compliance, ethical data sourcing, and employee data literacy.

Empowering employees to understand how their data is used can support DEI efforts and build a culture of trust around AI implementation.

1.4.3 Accountability and Legal Responsibility

AI systems introduce ambiguity around liability. When an autonomous system causes harm-such as an incorrect medical diagnosis or a discriminatory hiring decision-responsibility may be unclear. Is it the developer, the deploying organization, or the algorithm itself?

Legal scholars argue for updated liability frameworks that reflect the emergent agency of AI systems. This includes audit trails, impact assessments, and regulatory sandboxes for experimentation under supervision (Pagallo, 2013; Lin, 2020). The European Commission's proposed AI Act (2021) reflects this trend, introducing risk-based classifications and mandatory transparency obligations for high-risk applications.

Strategically, businesses must not treat AI ethics as an afterthought but as an embedded component of enterprise risk management. Governance boards, ethics committees, and cross-functional reviews should be part of AI deployment pipelines, particularly for decision-critical tools in HR, finance, and public-facing services.

1.4.4 Moral Norms, Social Expectations, and DEI Sensitivity

Beyond legal compliance, ethical implementation must align with informal norms and societal values. Cultural expectations, moral worldviews, and emotional responses to automation shape public trust-and thus determine adoption success.

For instance, while robotic assistants in eldercare may be efficient, they often raise concerns about human dignity, emotional neglect, and the replacement of care work, especially in cultures that emphasize familial responsibility (Sparrow, 2006). Similarly, AI that replaces front-line retail roles may trigger resentment in economically vulnerable communities if not accompanied by reskilling programs and equitable opportunities.

To address these tensions, organizations should adopt participatory design principles engaging employees, customers, and affected communities in the development and deployment of AI systems. This approach fosters organizational legitimacy, improves adoption outcomes, and supports the strategic goals of diversity, equity, and inclusion.

1.4.5 Strategic Implementation: From Ethics to Competitive Advantage

When applied responsibly, ethical AI can become a source of strategic differentiation. Firms that lead in ethical innovation such as Patagonia, Salesforce, and Microsoft-enjoy higher employee engagement, customer trust, and regulatory goodwill (Accenture, 2022).

Ethical principles must be linked to decision-making structures through the creation of AI ethics frameworks, training in responsible AI, and cross-departmental governance teams. Leadership commitment is crucial: without C-suite endorsement, ethics programs risk becoming symbolic rather than structural.

Moreover, integrating ethics into AI literacy training helps employees better understand both the potential and limits of automation, fostering critical engagement and human-centered design. As AI adoption deepens, companies that align ethics with operational agility are more likely to sustain inclusive innovation and long-term competitive advantage.

Ethical and regulatory considerations are no longer peripheral to technological strategy-they are central to responsible and sustainable AI integration. Businesses that recognize this will not only avoid legal pitfalls and reputational risks but will cultivate trust, equity, and strategic coherence in an era increasingly defined by data-driven decision-making.

Just as automation transforms workflows, ethics must transform how organizations think about responsibility, fairness, and the future of work.

1.5 Business Sustainability and Technological Integration: Sector-Specific Applications of AI and Automation

Artificial Intelligence (AI) and automation are no longer confined to isolated technical functions; they are now embedded within the strategic architecture of entire industries. From healthcare and public governance to manufacturing and finance, these technologies are reshaping business models, reconfiguring labor markets, and demanding new organizational capabilities. This section explores the sectoral implications of AI and automation with a focus on business strategy, employee reskilling, and inclusive innovation.

AI and automation are advancing corporate sustainability goals. These technologies optimize energy use, reduce waste, and enhance operational efficiency. AI-enabled systems can analyze supply chain data to identify inefficiencies, while automation reduces human error and overproduction (Ghahramani et al., 2020; Muller et al., 2020).

Technological agility, supported by AI, allows firms to respond swiftly to market volatility, regulatory changes, and consumer expectations. This adaptability not only enhances competitiveness but also promotes long-term business resilience-a key tenet of sustainable growth strategies.

1.5.1 Manufacturing and Logistics

Manufacturing has long been a focal point of automation, and AI technologies have significantly accelerated productivity gains. In advanced manufacturing settings, AI tools such as predictive maintenance and computer vision systems are deployed to optimize production workflows and reduce inefficiencies (Lee et al., 2014). Companies like Siemens and General Electric have embraced digital twins-virtual replicas of physical assets-to simulate and optimize manufacturing processes in real time.

McKinsey (2024) highlights how leading firms are now combining AI with industrial IoT (Internet of Things) and cloud computing to scale operational intelligence globally. For example, manufacturers are deploying AI-powered quality control systems that reduce defects and energy consumption.

Logistics firms utilize AI technologies for optimizing delivery routes, forecasting inventory demand, and automating warehouse operations (Chui et al., 2018)

Strategically, these transformations require businesses to reskill employees in areas like industrial data analytics, human–robot collaboration, and systems monitoring. Partnerships with technical schools and internal training academies are vital to bridge skill gaps and retain human capital in increasingly automated settings (World Economic Forum, 2023).

1.5.2 Healthcare and Public Services

Healthcare is undergoing a paradigm shift via AI applications in diagnostics, imaging, and clinical workflows. Machine learning models now outperform humans in specific diagnostic tasks such as identifying retinal diseases or analyzing chest X-rays (Esteva et al., 2017; Gulshan et al., 2016). McKinsey (2024) notes how AI is revolutionizing drug discovery and personalized treatment, citing examples like Insilico Medicine's, also known as "computational medicine", use of generative AI to design novel molecules in record time.

Robotic-assisted surgery, as seen in platforms like da Vinci, enables minimally invasive procedures with higher precision and reduced recovery times (Yang et al., 2020). In public health, AI supports epidemic forecasting, health system optimization, and vaccine supply management-capabilities proven vital during the COVID-19 pandemic (Nguyen et al., 2021).

These innovations require workforce reskilling in data interpretation, digital ethics, and AI-human co-decision-making. Health organizations must embed digital competencies into professional development while ensuring transparency and patient trust. Strategically, AI adoption also calls for leadership alignment with regulatory frameworks and equitable care standards.

1.5.3 Financial Services and Banking

The financial sector is increasingly defined by AI. From algorithmic trading to customer personalization, firms are using AI to improve operational resilience and client experience. Many financial institutions are now leveraging real-time AI-powered anomaly detection systems to significantly reduce fraud-related losses, illustrating the strategic value of AI in high-risk operations (Davenport & Ronanki, 2018).

Natural language processing (NLP) now enables automated regulatory reporting and contract review, reducing compliance costs. Robo-advisors and AI-driven portfolio optimization are reshaping wealth management (Vučinić & Luburić, 2024 JPMorgan Chase has made strides in AI through its Contract Intelligence (COiN) platform. By employing AI to interpret and review legal documents, COiN can analyze thousands of contracts within seconds. This capability dramatically reduces the time and resources needed for contract analysis, previously requiring approximately 360,000 labor hours annually (IBM Research). Moreover, the platform has enhanced the accuracy of data extraction, leading to better compliance and risk management processes.

These transformations underscore the need for hybrid roles in finance and data science. Business leaders must invest in strategic reskilling programs that integrate data literacy, compliance, and ethical AI governance. DEI considerations must also guide hiring and upskilling to avoid reinforcing systemic bias through data-driven decision tools.

1.5.4 Education and Skills Development

AI is driving a new era of adaptive and personalized learning. Platforms like Khan Academy and Coursera use machine learning to tailor curricula and assessments in real time (Luckin et al., 2016). According to McKinsey (2024), institutions are now embedding AI not just into digital pedagogy, but also into administrative workflows and student performance forecasting.

For employers, the strategic imperative is clear: close the skills gap by co-developing curricula with educators and investing in internal learning ecosystems. Global reskilling initiatives from firms like IBM and PwC focus on digital literacy, cloud computing, and responsible AI use-preparing both technical and non-technical staff for future work environments.

Education-business collaboration must also champion DEI by ensuring underrepresented groups have access to AI training, fostering inclusive growth in the digital economy.

1.5.5 Retail, Customer Service, and E-Commerce

AI is transforming consumer engagement through hyper-personalized experiences. Recommendation engines, chatbots, and intelligent pricing algorithms drive conversion and retention in e-commerce (Gómez-Uribe & Hunt, 2015). According to McKinsey (2024), retail leaders are using AI to reduce returns, personalize promotions, and optimize inventory-translating to significant profit gains.

Virtual agents now manage high volumes of customer interactions, while computer vision tools help monitor foot traffic in physical stores. AI also powers sentiment analysis to guide marketing campaigns in real time.

Strategically, these changes demand cross-training in CRM software, AI ethics, and human-machine interaction. Companies must encourage employee buy-in by framing AI as an augmenting-not replacing-tool, and by ensuring that frontline staff share in productivity gains through reskilling and incentives.

1.5.6 Government and Governance

Governments are increasingly leveraging AI to enhance public service delivery-from automated tax processing to transportation optimization and digital identity verification (Gharaibeh et al., 2017). McKinsey (2024) points to examples like Singapore's use of AI to optimize urban planning and Brazil's application of AI to detect irregular public spending.

However, public adoption must be balanced with ethical oversight. Technocratic governance risks excluding vulnerable populations if digital divides persist. Transparency, accountability, and civic consultation must guide implementation.

Civil servants require continuous training in data protection, ethical AI use, and algorithmic accountability. Strategic digital transformation should prioritize public trust and equity, especially as AI tools begin influencing justice, education, and healthcare policy decisions.

Across industries, AI and automation are catalysts of structural transformation and strategic reinvention. However, their effectiveness depends on more than technology-it requires forward-thinking leadership, cross-sector collaboration, inclusive upskilling efforts, and the creation of ethical ecosystems that prioritize social value alongside economic returns.

Despite success stories, a significant gap remains in understanding how organizations can strategically coordinate AI integration with employee motivation, inclusive talent strategies, and real-time decision-making (DSM) systems. As McKinsey (2024) notes, the winners in AI adoption are not necessarily those with the best algorithms, but those with the clearest strategic vision, strongest change-management processes, and deepest investments in human capital. Organizations that invest in reskilling, support DEI in digital adoption, and align AI strategy with business purpose are more likely to thrive in the emergent future of work.

The integration of artificial intelligence (AI) into the workforce presents both significant opportunities and critical challenges. On the one hand, AI has the potential to enhance productivity by automating repetitive tasks, supporting human decision-making, and enabling workers to focus on higher-value activities. These improvements could lead to increased wages and economic growth (OECD, 2019). On the other hand, AI may also displace jobs, particularly among low-skilled workers, and exacerbate income inequality due to uneven access to reskilling opportunities. Moreover, there is concern that monopolistic control of AI technologies by a few firms could reduce market competition and increase systemic risks in times of economic downturn (OECD, 2019).

Table 1: Opportunities and Threats of Using AI

1. Productivity

Opportunities of Using AI	**Threats of Using AI**
Potential for global rise of productivity	Substitute for humans
Possibility of higher wages and incomes	Favoring skilled over unskilled labour
Complementing people at performing activities	Favoring automation rather than human-complementary technologies
Automation provides workers with the ability to perform more requiring activities	Potential for upsurge of job losses in cognitive occupations as well
Improving the lives of people due to automation of activities	Worsening labour income when AI overtakes jobs
Greater the adoption of AI tools in economy,	Raising wealth inequality

Opportunities of Using AI	Threats of Using AI
greater the effects to productivity	
	Few firms' monopolistic position
	AI algorithms can trigger forecasting errors in the downturn

2. Labour Market and Employee Efficiency

Opportunities of Using AI	Threats of Using AI
Releasing employees from doing daily repetitive tasks	More replaceable workers
Support employees to perform higher-productivity tasks	Ability to affect cognitive jobs
Substitute for exhausting paperwork	Reduced labour demand and hiring
Boosting efficiency	Extraordinary job losses
Potential for wages' growth	Lower wages and rising inability to pay debts

Opportunities of Using AI	Threats of Using AI
Reskilling and upskilling of existing workforce	Disproportionate rise of income
Employment of technologically skilled and qualified generations	Exacerbating inequality
Building innovation supportive culture in organisations	Raise of long-term unemployed people lacking the necessary skills
	Allocation of experts from academia to industry
	Deepening of social tensions

CHAPTER 2: RESEARCH METHODOLOGY

This chapter presents the methodological framework used to examine the impact of automation and artificial intelligence (AI) on the future of work, with a focus on strategic integration across diverse sectors. The research follows a positivist, quantitative approach and outlines the philosophical positioning, research design, methodology, instrument development, sampling strategy, data analysis techniques, and ethical safeguards.

2.1 Research Philosophy

This study follows a realist ontological stance, viewing AI-driven organizational change as objectively real and measurable-a viewpoint aligned with positivist research traditions (Bryman, 2017).

2.2 Research Paradigm

Situated within the positivist research paradigm, this study prioritizes objectivity, deductive reasoning, and hypothesis testing through structured instruments. The positivist stance enables the investigation of how automation and AI affect strategic dimensions of work and workforce planning by analyzing patterns using statistical methods (Creswell & Poth, 2016).

2.3 Research Design

This study employs a quantitative, cross-sectional, and explanatory research design to investigate employees' perceptions across various sectors concerning the integration of artificial intelligence (AI) and its implications for the future of work. The design is shaped by the goal of identifying and analyzing the relationships between AI implementation and key strategic dimensions, including ethical concerns, organizational sustainability, and workforce transformation.

A cross-sectional research design involves collecting data from a defined population at a single point in time. This approach enables the researcher to capture a “snapshot” of existing attitudes and perceptions without manipulating the research environment (Setia, 2016). Cross-sectional research is often employed in social sciences due to its efficiency in capturing present attitudes and behaviors across varied respondent groups (Creswell & Creswell, 2018; Setia, 2016). In this study, it provides a timely overview of employee insights across multiple sectors where AI and automation are currently being deployed.

The explanatory (or causal-comparative) element of the design serves to explore not only descriptive patterns but also potential causal or correlational relationships between variables. This includes hypothesis testing regarding how AI-related constructs-such as strategic integration, perceived ethical risks, and the adoption of automation-affect workforce perceptions and anticipated organizational changes. Explanatory research is well-suited for studies aiming to evaluate cause-and-effect dynamics without experimental intervention (Bryman, 2016).

Following Robson’s (2011) framework, this design fulfills a threefold research purpose:

Descriptive: To document the demographic and organizational characteristics of the sample.

Analytical: To evaluate statistical relationships among variables related to AI integration.

Explanatory: To test whether specific AI-related factors predict anticipated changes in the structure or nature of work.

In addition, this design supports a degree of generalizability, especially given the study’s sample size (n = 122) and inclusion of participants from a range of industries. The structured nature of the design enables the use of statistical software (SPSS) to conduct regression analysis, assess internal reliability, and explore variable associations with a high degree of rigor.

In summary, the cross-sectional, quantitative, and explanatory research design offers a robust and coherent framework for addressing the strategic impact of AI technologies in contemporary work environments. It aligns well with the study’s positivist paradigm, enabling data-driven, hypothesis-oriented inquiry and supporting conclusions that are both empirical and generalizable.

2.4 Research methodology

This study uses a quantitative research approach, structured to reveal the attitudes and perceptions of a specific target audience regarding the integration of technologies in human resource management, with a particular focus on artificial intelligence. The goal of quantitative research is the systematic investigation of phenomena using statistical techniques and numerical data. It is based on a representative sample of observations, with the intention that these findings reflect the wider population. For this investigation, quantitative research was chosen due to its suitability, as it emphasizes numerical data that yields valuable statistics. This approach is particularly effective in identifying patterns or behaviors in a sample population. In addition, quantitative research produces reliable, measurable, and verifiable data, which is crucial when evaluating the effectiveness of AI applications in human resource management. The results obtained from quantitative research can be extended to larger samples or populations, thus enhancing the applicability of the findings on a wider scale (Rabianski, 2003).

Quantitative-type methodology facilitates data collection in a more objective manner, thus reducing personal biases and interferences that could affect the research process. The use of statistical tools facilitates the analysis of data, thus providing a deeper understanding of trends, correlations and predictions related to artificial intelligence in the field of human resource management. Accurate measurement of quantitative variables is essential to understanding the impact of artificial intelligence on human resource management. In summary, the application of quantitative methodology significantly improves the caliber of research on the application of artificial intelligence in business management by providing reliable, objective and reliable data and findings. This approach aims to identify the factors responsible for changes in social phenomena, trying to confirm (or refute) an existing hypothesis through the use of numerical data and statistical analysis (Field, 2013).

2.5 Questionnaire Development

A structured questionnaire was designed and divided into six sections:

1. Demographics
2. AI & Automation: Security and Ethics (8 items)
3. AI in Organizational Sustainability (6 items)
4. Social and Ethical Impacts (3 items)
5. Strategic Integration of AI (4 items)
6. AI and the Future of Work (12 items)

A 5-point Likert scale was used throughout (Likert, 1932), ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). This approach allowed for standardized quantification of attitudes and perceptions across a wide participant base (Joshi et al., 2015). Questionnaire content was informed by prior validated studies and adapted to the context of AI in government organizations.

2.5.1 Demographics

Basic demographic and professional information were gathered, such as age, gender, level of education, company's activity sector, representation of role within the organization, years of professional experience, company's current employee dynamics, use of artificial intelligence and automation in company

2.5.2 AI in Organizational Sustainability

In this section of questionnaire, perception of AI & Automation on Security and Ethics was assessed. Using a 5-point Likert scale the sample expressed their level of agreement on 8 statements relevant to AI & Automation, Security and Ethics. More specifically improvement of the accuracy of workplace processes, improvements of efficiency and the elimination of repetitive and time-consuming tasks, as well as enhancement of security etc.

2.5.3 Artificial Intelligence & Automation in Organizational Sustainability

With the term organizational sustainability, is about equipping organizations with the prople and stuctures necessary for success in the global marketplace of the 21st Century. Organizational sustainability and impact of Automation and AI was assessed with 5-point Likert Scale varying from Strongly Disagree to Strongly Agree. Reducing personnel costs and improvement of resources allocation via AI, as well as enhancement of productivity and maintenance of quality standards, was assessed.

2.5.4 Social and Ethical Impacts of AI and Automation

Social and Ethical Impacts of Automation and AI refer to workforce inequalities, proactive measures to ensure inclusivity and fairness and regulation of AI and Automation. All of the above were assessed with the use of a 5-point Likert Scale.

2.5.5 Strategic Integration of AI and Automation

Strategic Integration of AI and Automation refers to a well-communicated strategy for integrating AI and Automation, adopting AI implementation costs etc. 5-point Likert scale was used.

2.5.6 AI and Automation impact on Human Resources and the Future of Work

The future of work is through AI and Automation is the creation of new roles requiring advanced technological skills, training and developing opportunities, creativity and innovation in workplace teams, flexibility of tasks etc. A 5-point Likert Scale was as well used varying from Strongly Disagree to Strongly Agree.

2.6 Data Collection

Collecting data is a necessary component since there is no research that does not contain and does not include the appropriate data to analyze it. Primary type research serves as the initial source for information. This category includes methods such as observation, interview, experiment and focus group. In contrast, secondary data comes from existing materials that have already disseminated information, among which sources include books, articles, newspapers and magazines. The primary type of data requires significant commitment and requires focused dedication, while the secondary type of data does not require direct engagement with the subject. Consequently, this research uses secondary materials to obtain data. The main justification for choosing secondary sources in data lies in their enhanced relevance to the researcher's specific requirements, as opposed to primary research, which often lacks such specificity. (Bryman, 2017).

An important justification for using primary data lies in its recognition as a highly authentic source. These sources offer information on current types of events and information related to specific types of topics. Consequently, data collected from primary sources have the recognition of reliability because of their objective characteristics and direct collection from the original source. Therefore, this research preferred to make use of primary data. In this study, a survey was first distributed to each participant, with the aim of assessing the impact of artificial intelligence on future employment. Collectively, primary sources offer increasingly valuable perspectives on the implications of artificial intelligence. The thinking behind choosing this type of primary sources is their cost effectiveness and their ability to identify data in an unbiased manner.

In this research, a large number of sources were used, including research articles, books and official reports issued by the European Commission. In order to accurately reflect the current employment landscape in Greece, we created a precise timeline for our data selection criteria, covering the years up to 2025. The evaluation effort for these studies was guided by two key factors, being relevant to the research our research and how often they refer to other academic sources. Furthermore, the researcher took into account a number of additional and important factors, including the geographical context of the surveys.

Saunders et al. (2012) describe a sample as a subset of a population selected to represent the whole in research analysis. Additionally, the study argued that for research findings to be generalized, the sample must adequately represent the entire population. This study aims to examine the impact of artificial intelligence on the future of employment in government organizations. To achieve this goal, the current sample consists of civil service employees. The data is mainly collected from those businesses where artificial intelligence has been integrated into routine tasks. Quantitative data is obtained through a survey conducted by these employees with the aim of gaining deeper insights into their experiences. 122 employees are being investigated. The rationale for choosing this sample (at least one hundred people), is its relevance to the aims and purposes of the study. Consequently, this sample size and composition contributes significantly to the fulfillment of the research objective.

The participant recruitment technique used in this study is purposive sampling. According to Etikan, Musa, & Alkassim (2016), the method of purposive sampling is considered as a sustainable strategy, characterized by the participant's logical judgment based on his experience about a kind of specific phenomenon, topic or concept. Their research also showed that the primary focus of this approach should not be overly focused on sample characteristics. Consequently, this sampling technique has facilitated the recruitment of people employed in government organizations that have incorporated artificial intelligence. In addition, this method helps the writer to address the research question. Bryman (2017) noted that purposive sampling possesses significant advantages, among which is its ability to allow the researcher to explore the meaningful impact of findings on the sample. The Rabianski (2003). He further argued that the purposive sampling technique is widely regarded as the most effective type of method, mainly due to its time and cost efficiency compared to alternative sampling approaches.

2.7 Data Analysis

Data collected through questionnaires administered through the online platform Google Forms were organized into a spreadsheet (Excel) before being entered into the Statistical Package for Social Sciences (SPSS) for analysis. Descriptive statistics were used to examine the data, with a level of statistical significance set at $\alpha=0.05$ for all controls. Additionally, an internal consistency assessment was conducted using Cronbach's alpha method. In the field of academic research, a value exceeding 0.70 is considered acceptable. To assess the reliability of the Likert scale questions within the questionnaire, the Cronbach's alpha index from the SPSS statistical tool was used, which assesses the stability of participants' responses to the same scale in the absence of any intervening factors affecting their responses.

2.8 Reliability and Validity

To ensure the quality and credibility of the research findings, this study thoroughly addresses both reliability and validity, which are fundamental criteria for assessing the rigour of quantitative research instruments (Creswell & Creswell, 2018; Bryman, 2016).

2.8.1 Reliability

Reliability refers to the consistency, stability, and repeatability of a measurement instrument. In other words, a reliable instrument will yield the same results under consistent conditions over time (Tavakol & Dennick, 2011). In the context of survey research, reliability is crucial because it ensures that the constructs being measured-such as attitudes toward AI or perceptions of strategic integration-are not distorted by random error or inconsistency in the questionnaire design.

The most commonly used indicator of internal consistency reliability is Cronbach's alpha (α). This coefficient evaluates the degree to which items within a scale are correlated and thus measure the same underlying construct. Values of α above 0.70 are typically considered acceptable, while values above 0.80 or 0.90 are considered good to excellent (Field, 2013; Nunnally & Bernstein, 1994).

This study achieved a high degree of internal reliability, with Cronbach's alpha α=0.943. Cronbach's alpha for each subscale of the questionnaire is depicted at the following table:

Table 2: Cronbach's a for the subscales

Scale	**(N)**	**Alpha**
Artificial Intelligence & Automation, Security and Ethics	8	0.799
Artificial Intelligence & Automation in Organisational Sustainability	6	0.890
Social and Ethical Impacts of AI and Automation	3	0. 613
Strategic Integration of AI and Automation	4	0.654
AI and Automation impact on Human Resources and the Future of Work	12	0.875

From Table 2 we can conclude that the internal reliability of the scales is considered satisfactory as it ranges between 0.613 and 0.890.

Although the Social and Ethical Impacts (α = 0.613) and Strategic Integration (α = 0.654) subscales fall slightly below the 0.70 threshold, they are considered acceptable for exploratory studies, especially when constructs are broad or measured with few items (Hair et al., 2010).

2.8.2 Validity

Validity refers to the degree to which a research instrument accurately measures what it is intended to measure (Heale & Twycross, 2015). While reliability pertains to consistency over time and across conditions, validity concerns the appropriateness, relevance, and correctness of interpretations drawn from the instrument's results.

Several types of validity are relevant to this study:

a) Content Validity

Content validity assesses whether the questionnaire items comprehensively represent the entire domain of the construct (Bolarinwa, 2015). In this research, content validity was supported through:

- A review of existing literature to identify dimensions associated with AI and automation
- Adaptation of survey items from previously validated instruments

This process ensured that key themes-including ethical considerations, strategic integration, and workforce transformation-were well represented.

b) Face Validity

Face validity evaluates whether the instrument appears, on the surface, to measure what it intends to (Neuman, 2014). Though subjective, it is important for participant engagement. In this study, face validity was established by:

- Conducting a pilot test with individuals working in AI-integrated sectors

- Gathering feedback that confirmed the clarity, logical structure, and relevance of survey items

c) Construct Validity

Construct validity tests how well the instrument captures the theoretical constructs it aims to measure (Bryman, 2016). It includes:

- Convergent validity, inferred from high internal consistency (Cronbach's alpha values) among related items
- Discriminant validity, though not statistically tested via factor analysis due to sample limitations, was addressed by clearly differentiating conceptual domains during survey design

d) Criterion Validity

Criterion validity examines the correlation between the instrument and an external standard. While no benchmark tool was applied in this study, conceptual alignment with validated theoretical frameworks supports the instrument's theoretical robustness (Field, 2013).

2.9 Ethical Considerations

In accordance with established ethical standards governing research involving human participants, all necessary precautions were taken to ensure that participants were not exposed to harm, discomfort, or undue pressure. Particular care was given to the design of the questionnaire to ensure that no intrusive or coercive questions were included, thereby safeguarding participants from being compelled to disclose information they might wish to keep private. The study's primary focus - the strategic impact of AI and automation in the workplace - was addressed in a manner that prioritized participant autonomy and psychological comfort. Questions were formulated neutrally to avoid emotional distress or reputational risk. In addition, participants were informed of their right to decline participation or skip any questions they did not wish to answer. This ethical stance was maintained to uphold the principle of non-maleficence and to prevent any adverse effects during or after participation (Rabianski, 2003). Overall, the design of the study reflected a commitment to the dignity, rights, and welfare of all respondents, in line with best practices in research ethics.

CHAPTER 3: RESULTS AND FINDINGS

In the following chapter we are going to demonstrate the main results deriving from the statistical analysis of the data.

3.1 Demographics

Demographical frequencies and relative frequencies are depicted at Table 3:

Table 3: Frequencies and relative frequencies of demographical characteristics

	N	(%)
Gender		
Woman	79	64.8%
Man	42	34.4%
Other	1	0.8%
Age		
20-34	7	5.7%
35-44	37	30.3%
45-54	47	38.5%
55+.	25	20.5%
Studies		
Hish School/ college, diploma or equivalent	17	13.9%

Bachelor's degree	29	23.8%
Master's degree	64	52.5%
PhD	12	9.8%
Work Experience		
Less than a year	2	1.6%
1-5 years	30	24.6%
6-10 years	21	17.2%
More than 10 years	69	56.6%
Employees of working company		
1-10	38	31.1%
11-50	29	23.8%
51-250	22	18.0%
251+	33	27.0%

From the Table 3 we and conclude that the majority of the sample were women with the relative frequency of women reaching 64.8% (79 women), while the remaining 34.4% were man (42 men). The 0.8% was of other gender (1 person), as depicted at the following pie chart:

The largest portion of the sample falls within the 45–54 age group, representing 38.5% (47 individuals). This is followed by participants aged 35–44 at 30.3% (37 individuals), those aged 55 and over at 20.5% (25 individuals), and the 20–34 age group at 5.7% (7 individuals).

Regarding educational background, 52.5% of participants (64 individuals) hold a master's degree, while 23.8% (29 individuals) have a bachelor's degree. A further 13.9% (17 individuals) completed high school or hold a diploma or equivalent qualification, and 9.8% (12 individuals) possess a PhD. The distribution of educational attainment is illustrated in Figure 4:

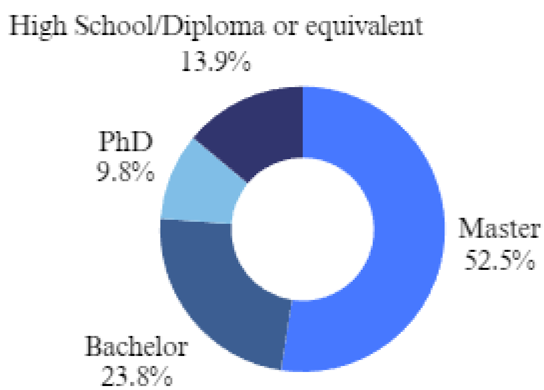

Figure 4: Relative frequencies of educational level

Sample's work experience is more than 10 years for the majority of the sample, with the relative frequency reaching 56.6% (69 people), while 1-5 years' work experience is referred by 24.6% of the sample (30 people) followed by 6-10 years' work experience that is referred by the 17.2% (21 people). Lastly less than 1 year of work experience is being referred by 1.6% of the sample (2 people). Samples work experience is depicted in Figure 5.

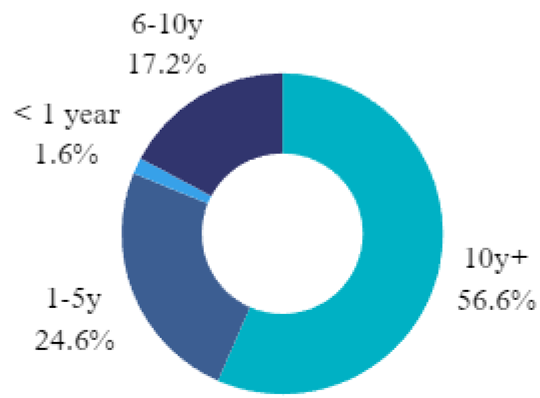

Figure 5: Work Experience (years)

In response to the question "How many employees does your current company have?", the results indicate a diverse distribution across company sizes. Specifically, 27.0% of respondents (33 individuals) reported working in companies with more than 250 employees. Another 23.8% (29 individuals) indicated that their company employs between 11 and 50 people. Companies with 51 to 250 employees were reported by 18.0% of the participants (22 individuals), while the largest group, comprising 31.1% of respondents (38 individuals), reported working in small companies with 1 to 10 employees. The distribution of company sizes is illustrated in Figure 6.

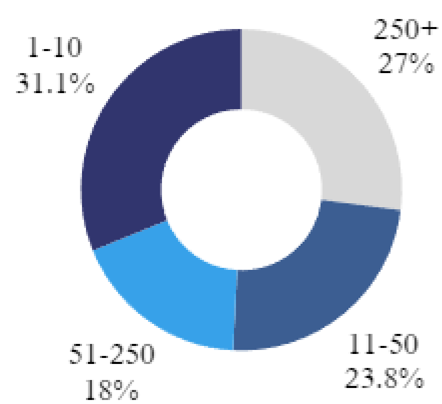

Figure 6: Employees at the working company

The company's activities sector is shown in Table 4:

Table 4: Sector of the company's activities

Sector	N
Transportation and Logistics	*3*
Telecommunications	*1*
Software	*1*
Retail	*6*
Research in Physics	*1*
Research Centre	*1*
Manufacturing	*1*
Legal services	*1*
Insurance	*1*
Information technology (ICT)	*10*
HVAC	*1*
Hospitality and Tourism	*6*
Healthcare	*6*
Government and Public Administration	*10*
Financial Sector	*7*
Esthetician	*1*
Environmental and green energy	*1*
Entertainment and Media	*2*
Electrical Sector	*2*
Education Sector	*19*

Digital Marketing/advertising	*2*
Design and Sales	*1*
Consulting services	*8*
Non-profit and Social Services	*6*
Research	*3*
Public Sector	*2*
Pharmaceutical and Biotechnology	*1*
Construction	*8*
Agriculture / Food	*6*
Aerospace and Defense	*2*
Energy Sector	*1*
Inspection certification training	*1*
Academic	*1*

At the following question, responders were asked to state their role in the organization, with the frequencies as depicted at Table 5.

Table 5: Role in the organization

Role	N
Administrative/ Support	*10*
Customer Service	*4*
Design	*6*
Education/ Training	*12*
Executive/ Managerial	*17*
Finance/ Accounting	*10*
Healthcare	*3*
Human Resources	*2*
IT/ Computing	*9*
Legal	*1*
Operations/ Production	*7*
Other	*6*
Professional/ Technical	*11*
Public Relations/ Communications	*7*
R & D	*5*
Sales/Marketing	*12*

3.2. AI and Automation, Security and Ethics

As stated before, in order to assess the Security and Ethics of AI and Automation, the sample expressed their level of agreement or disagreement, on a 5-item Likert scale that ranged from Strongly Disagree, to Strongly Agree. The scale was calibrated from 1 to 5 as follows: 1: Strongly Disagree, 2: Disagree, 3: Neither agree, nor disagree, 4; Agree, 5: Strongly Agree, while the min, max and mean value for each statement of the scale is as depicted at Table 6:

Table 6: Mean and standard deviation of security and ethics of AI and Automation

	Mean	Std. Deviation
AI and automation reduce human error and improve the accuracy of workplace processes.	3.57	0.900
AI-driven automation improves efficiency by eliminating repetitive and time-consuming tasks.	4.03	0.890
Automated and AI-supported data checks enhance security and minimize risks such as fraud.	3.39	0.886
AI systems are more reliable than human verification for certain tasks.	2.87	0.970
AI and automation increase transparency in organizational decision-making and operations.	3.16	0.891
I feel supported in adapting to AI and automation in my role.	3.06	1.242
I am confident that my organization prioritizes ethics in AI and automation decisions.	3.00	1.171
My organization has a clear regulatory framework for the ethical implementation of AI and automation technologies.	2.74	1.112

Regarding AI and Automation, security and ethics, we can conclude that the research participants seem to mostly believe that AI- driven automation improves efficiency by eliminating repetitive and time-consuming tasks (4.03/ 0.890) while it reduces human error and improves the accuracy of workplace processes (3.57/0.900). Moreover, Automated and AI supported data checks enhance the security and minimize risks such as fraud (3.39/ 0.886).

Sample seemed neutral regarding, the increase of transparency in organizational decision making and operations (3.16/ 0.891), while AI systems seemed not to be more reliable than human verification for certain tasks (2.87/0.970).

Participants in the study seemed to be mostly neutral regarding the prioritization of ethics in Ai and automation decisions in the organization (3.00/1.171), and the clear regulatory framework for the ethical implementation of AI and automation technologies (2.74/ 1.112). The support in adapting to AI and automation in the samples role in the organization was also close to neutral (3.00/ 1.171).

Following on, we are going to examine differences in attitudes and beliefs towards AI and Automation, security and ethics according to gender, Age category, Studies, Work Experience and number of employees. Categories with little representatives were excluded from the analyses in order to retain their statistical power. Independent samples t-test and Analysis of variation were conducted with the results shown at Table 7:

Table 7: Mean values, t-test and ANOVA for Security and Ethics among demographic categories

	Mean	Standard deviation	t-test/ ANOVA
Gender			
Male	3.19	0.717	t=-0.615 df=119 p=0.540
Female	3.28	0.533	
Age level			
20-34 (n=7)	3.3036	0.74602	F (3, 115) = 0.167 p=0.918
35-44 (n=37)	3.1757	0.76346	

45-54 (n=47)	3.2580	0.53632	
55+ (n=25)	3.2550	0.52599	
Studies			
High School/ college graduate, diploma or equivalent	3.3162	0.50605	F (3, 121) = 0.398 p=0.755
Bachelor's degree	3.2845	0.72418	
Master's Degree	3.1641	0.66027	
PhD	3.2813	0.68491	
Work Experience			
1-5 years	3.2625	0.78876	F (2, 119)=1.417 p=0.247
6-10 years	3.0060	0.55688	
More than 10 years	3.2754	0.62227	
Number of employees			
1-10	3.2664	0.75347	F (3, 121)=0.536 p=0.659
11-50	3.1724	0.54426	
51-250	3.1023	0.73359	
251+	3.3068	0.57630	

From Table 7 we can conclude that there is no statistically significant difference for samples attitudes and beliefs towards security and ethics for the demographic categories of gender, Age level, Studies, Work experience and Number of employees.

3.3 AI and Automation in organizational sustainability

Following on, the application of AI and Automation in organizational sustainability was assessed with the use of a 5-polit Likert scale. The mean value and standard deviation were calculated, and are depicted at Table 8:

Table 8: Mean and Standard deviation of AI and automation in organizational sustainability

	Mean	Std. Deviation
Unlike environmental sustainability, which is about the environment, organizational sustainability is about equipping organizations with the people and structures necessary for success in the global marketplace of the 21st century.	3.47	0.972
AI systems and automation tools enhance productivity and help achieve strategic goals.	3.74	0.898
AI and automation allow us to scale operations while maintaining quality standards.	3.58	0.841
AI fosters innovation and helps organizations develop competitive advantages.	3.65	0.961
AI-driven automation enables faster adaptation to market changes and external challenges, strengthening organizational resilience.	3.57	0.971
The use of AI supports long-term business sustainability and growth.	3.50	0.947

We can conclude that survey participants seem to relate with the belief that organizational sustainability is about equipping organizations with the people and structures necessary for success in the global marketplace of the 21st century (3.47/ 0.972). On the other hand, sample believe neutrally that AI systems and automation tools enhance productivity and help the achievement of strategic goals (3.74/ 0.898), while AI and automation allow scale operations while maintaining quality standards

(3.58/ 0.841)

AI fosters innovation and helps organizations develop competitive advantages (3.65/0.961) while AI-driven automation enables faster adaptation to market changes and external challenges, strengthening organizational resilience (3.57/0.971). Lastly, the use of AI supports long-term business sustainability and growth (3.50/0.947).

Next, we are going to examine the difference in samples attitudes and beliefs towards organizational sustainability, according to demographic characteristics. Mean values, standard deviation as well as t-test and ANOVA results were depicted at the following table:

Table 9: Mean values, t-test and ANOVA for Organizational Sustainability among demographic categories

	Mean	Standard deviation	t-test/ ANOVA
Gender			
Male	3.50	0.778	t=-1.526 df=119 p=0.130
Female	3.72	0.684	
Age level			
20-34 (n=7)	3.5238	0.70336	F (3, 115) =0.987 p=0.402
35-44 (n=37)	3.4775	0.88816	
45-54 (n=47)	3.6099	0.64669	
55+ (n=25)	3.8000	0.64190	

Studies			
High School/ college graduate, diploma or equivalent	3.5294	0.41765	F (3, 121) =0.364 p=0.779
Bachelor's degree	3.7011	0.65975	
Master's Degree	3.5651	0.84077	
PhD	3.4722	0.83434	
Work Experience			
1-5 years	3.4056	0.85398	F (2, 119) =2.220 p=0.113
6-10 years	3.4286	0.73328	
More than 10 years	3.7053	0.70081	
Number of employees			
1-10	3.6184	0.79969	F (3, 121) =1.820 p=0.147
11-50	3.7126	0.61865	
51-250	3.2576	0.73773	
251+	3.6465	0.77028	

From Table 9 we can conclude that there is no statistically significant difference for samples attitudes and beliefs towards organizational sustainability between the demographic categories of gender, Age level, Studies, Work experience and Number of employees.

3.4. Social and ethical impacts of AI and Automation

Social and ethical impacts of AI and Automation were assessed with the use of a 5-item Likert scale on three statements. Respondents imprinted grade of agreement or disagreeing, while the mean value and the standard deviation is as depicted at Table 10.

Table 10: Mean value and standard deviation of social and ethical impacts of AI and Automation

	Mean	Std. Deviation
AI and automation can lead to workforce inequalities	3.27	1.013
My organization takes proactive measures to ensure inclusivity and fairness in the adoption of AI-driven technologies.	2.77	0.934
I believe AI and automation should be regulated by external authorities or governments.	3.42	1.205

From the table above we can conclude that responders seem to neither agree, nor disagree with the belief that AI and automation can lead to workforce inequalities (3.27/ 1.013) as well as with the belief that AI and automation should be regulated by external authorities or governments (3.42/ 1.205).

On the other hand, responders seem to neither agree nor disagree, leaning to disagree with the belief that their organization takes proactive measures to ensure inclusivity and fairness in the adoption of AI-driven technologies (2.77/ 0.934).

In order to examine if there are differences in samples attitudes and beliefs regarding social an ethical impact of AI and Automation regarding the demographic characteristics, statistical tests of t-test and Analysis of Variance are going to be conducted, with the mean values and results showing in Table 11:

Table 11: Mean values, standard deviation and t-test, ANOVA results for the social and ethical Impacts of AI and automation regarding demographic characteristics

	Mean	Standard deviation	t-test/ ANOVA
Gender			
Male	3.20	0.623	t=1.476 df=119 p=0.143
Female	3.02	0.696	
Age level			
20-34 (n=7)	3.0000	0.90267	F (3, 115) =0.871 p=0.458
35-44 (n=37)	3.0631	0.65658	
45-54 (n=47)	3.2340	0.59756	
55+ (n=25)	3.2800	0.67823	
Studies			
High School/ college graduate, diploma or equivalent	3.4118	0.61835	F (3, 121) =1.314 p=0.273
Bachelor's degree	3.1954	0.75339	
Master's Degree	3.0938	0.59826	
PhD	3.0000	0.75210	

Work Experience			
1-5 years	3.0444	0.62351	F (2, 119) =2.412
6-10 years	2.9365	0.62021	p=0.094
More than 10 years	3.2560	0.67675	
Number of employees			
1-10	3.2105	0.68190	F (3, 121) =1.279
11-50	3.1724	0.66441	p=0.285
51-250	2.9091	0.77105	
251+	3.2323	0.52364	

From Table 11 we can conclude that there is no statistically significant differenceς for samples attitudes and beliefs towards social and ethical Impacts of Ai and Automation between the demographic categories of gender, Age level, Studies, Work experience and Number of employees.

3.5. Strategic integration of AI and Automation

Strategic integration of AI and Automation was assessed with the use of a 5-point Likert scale on four statements regarding the clear and well communicated strategy of the organization of AI and automation, challenges in adopting AI and Automation, while the mean values and the Standard deviation is depicted at Table 12:

Table 12: Mean value and standard deviation of strategic integration of AI and Automation

	Mean	Std. Deviation
My organization has a clear and well-communicated strategy for integrating AI and automation.	2.57	1.020
The biggest challenge in adopting AI and automation in my organization is resistance to change.	3.18	1.012
The biggest challenge in adopting AI and automation in my organization is lack of skills among employees.	3.20	1.140
The biggest challenge in adopting AI and automation in my organization is high implementation costs.	3.01	1.024

Sample seems to neither agree, nor disagree leaning to disagree with their organization having a clear and well communicated strategy for ingraining AI and automation (2.57/ 1.020).

The biggest challenge in adopting AI and automation seems to be the lack of skills among employees (3.20/ 1.140) followed by the resistance to change (3.18/ 1.1012), while the least significant challenge is high implementation costs (3.01/ 1.024). Mean values of challenges faced by the strategic integration of AI and Automation are depicted at Figure 7:

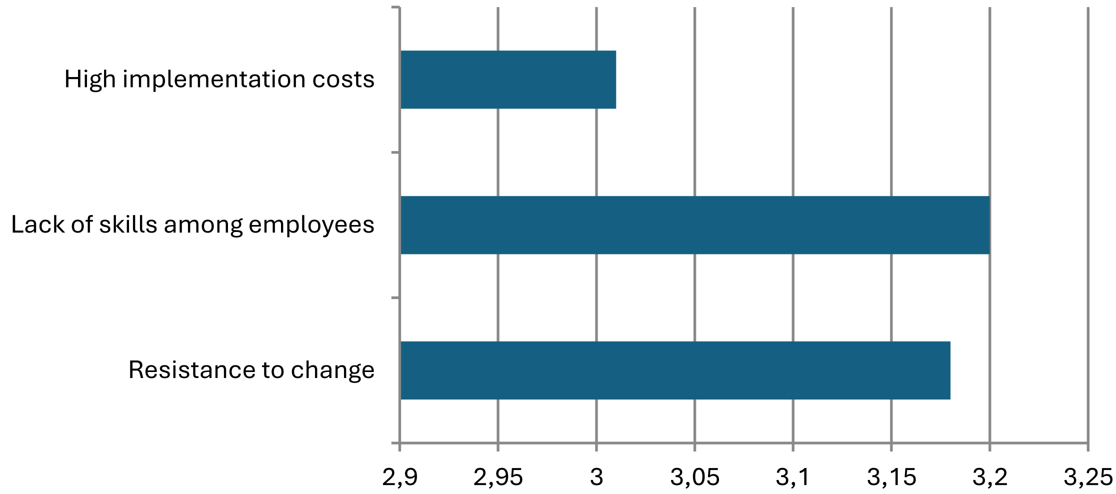

Figure 7: Mean value of challenges faced by the integration of AI and Automation to the work environment

Following on, we are going to examine differences between samples attitudes and beliefs towards the strategic integration of AI and Automation between the different levels of demographic categories. Mean values, as well as results of t-test and ANOVA are depicted at Table 13:

Table 13: Mean value, standard deviation and t-test/ ANOVA for strategic integration of AI and Automation between demographic categories

	Mean	Standard deviation	t-test/ANOVA
Gender			
Male	2.97	0.681	t=-1.338
Female	3.10	0.565	df=119 p=0.183
Age level			

20-34 (n=7)	3.0714	0.71755	F(3,115) = 0.561 p=0.642
35-44 (n=37)	2.8716	0.73035	
45-54 (n=47)	3.0426	0.57888	
55+ (n=25)	3.0100	0.60587	
Studies			
High School/ college graduate, diploma or equivalent	3.2500	0.53033	F (3, 121) =1.146 p=0.333
Bachelor’s degree	2.9828	0.66457	
Master’s Degree	2.9375	0.67700	
PhD	2.8958	0.55859	
Work Experience			
1-5 years	2.9500	0.64794	F (2, 119) =1.856 p=0.161
6-10 years	2.7500	0.65192	
More than 10 years	3.0543	0.63139	
Number of employees			
1-10	2.9803	0.81453	F (3, 121) =0.228 p=0.877
11-50	2.9914	0.53236	
51-250	3.0795	0.61907	
251+	2.9318	0.55295	

From Table 13 we can conclude that there is no statistically significant differenceς for samples attitudes and beliefs towards strategic integration of AI and Automation between the demographic categories of gender, Age level, Studies, Work experience and Number of employees.

3.6. AI and Automation impact on Human resources and the future of work

Impact of AI and Automation on Human resources and the future of work were assessed with a 5-point Likert scale. Sample reflected their extent of agreement or disagreement, while mean value and standard deviation are depicted at Table 14:

Table 14: Mean value and standard deviation of AI and automation on Human resources and the future of work

	Mean	Std. Deviation
AI and automation help create new roles requiring advanced technical skills.	3.62	0.982
AI enhances training and development opportunities for employees.	3.63	0.947
AI fosters creativity and innovation in workplace teams.	3.43	1.036
AI and automation enhance the ability of humans to focus on creative and strategic tasks.	3.62	1.007
AI and automation make my tasks more flexible and manageable.	3.75	0.887
AI and automation allow for greater flexibility in workforce management.	3.61	0.867
AI and automation increase stress and complexity in some roles.	3.15	1.088
I feel confident in adapting to the changes brought by AI and automation.	3.46	1.054
Employees are well-prepared for changes brought by AI and automation.	2.38	0.956

Information systems and AI-related technologies are essential skills for the future workforce.	3.99	0.932
Specializing in automation and AI technologies now seems like a promising career choice.	3.85	1.001
AI and automation can complement human work rather than replace it.	3.68	1.159
Information systems and AI-related technologies are essential skills for the future workforce.	3.99	0.932
Specializing in automation and AI technologies now seems like a promising career choice.	3.85	1.001
AI and automation can complement human work rather than replace it.	3.68	1.159

Sample seems to neither agree or disagree leaning towards agreement with the statement that Ai and automation help create new roles requiring advanced technical skills (3.62/ 0.982), the enhancement training and development of opportunities for employees (3.63/ 0.947) and the fostering of creativity and innovation in workplace teams (3.43/ 1.036). Moreover, sample seems to agree with the statement that AI and automation enhance the ability of humans to focus on creative and strategic tasks (3.62/1.007), make their tasks more flexible and manageable (3.75/0.887), permission of greater flexibility in workforce management (3.61/ 0.867) and, increment of stress and complexity in some roles (3.15/ 1.088).

Participants in the study neither agreed nor disagreed, leaning to agreeing with them feeling confident adapting to the changes brought by AI and automation (3.46/ 1.054) and being well prepared for changes brought by AI and automation. Summed to agree that information systems and AI-related technologies are essential skills for the future workforce. (3.99/0.932), specializing in automation and AI technologies now seems like a promising career choice (3.85/1.001) and AI and automation can complement human work rather has replace it (4.68/1.159).

In order to examine if there are differences in samples attitudes and beliefs regarding social an ethical impact of AI and Automation regarding the demographic characteristics, statistical tests of t-test and Analysis of Variance are going to be conducted, with the mean values and results showing in Table 15:

Table 151: Mean values, standard deviation and t-test, ANOVA results for the social and ethical Impacts of AI and automation regarding demographic characteristics

	Mean	Standard deviation	t-test/ANOVA
Gender			
Male	3.47	0.703	t=-0.839 df=119 p=0.403
Female	3.57	0.525	
Age level			
20-34 (n=7)	3.4286	1.04464	F (3, 115) =0.471 p= 0.703
35-44 (n=37)	3.4640	0.69125	
45-54 (n=47)	3.5638	0.56712	
55+ (n=25)	3.6333	0.44030	
Studies			
High School/ college graduate, diploma or equivalent	3.3971	0.50133	F (3, 121) = 0.283 p=0.838

Bachelor's degree	3.5603	0.71057	
Master's Degree	3.5352	0.64989	
PhD	3.4583	0.69857	
Work Experience			
1-5 years	3.4750	0.73538	F (2, 119) =1.866 p=0.159
6-10 years	3.2897	0.64475	
More than 10 years	3.5954	0.60504	
Number of employees			
1-10	3.5636	0.63003	F (3, 121) =0.407 p=0.748
11-50	3.5690	0.60013	
51-250	3.3939	0.65475	
251+	3.4899	0.71162	

From the table 15 we can conclude that there is no statistically significant differenceς for samples attitudes and beliefs towards social and ethical Impacts of Ai and Automation between the demographic categories of gender, Age level, Studies, Work experience and Number of employees.

Until now, five main factors of AI and automation have been reported: Security and Ethics, Organizational Sustainability, Social and Ethical Impacts, Strategic Integration and, Impact in HR and the future of work. Following on we are going to examine the correlation of participants' beliefs on those factors by calculating parsons (r) correlation coefficient, as depicted at the Table 16:

Table 16: Pearson's correlations for the scales of AI and Automation

	1	2	3	4	5
1. Security and Ethics	1	0.696**	0.314**	0.302**	0.587**
2. Organizational Sustainability	0.696**	1	0.121	0.373**	0.672**
3. Social and Ethical Impacts	0.314**	0.121	1	0.127	0.163
4. Strategic Integration	0.302**	0.373**	0.127	1	0.371**
5. Impact on Human Resources and the Future of Work	0.587**	0.672**	0.163	0.371**	1

**. *Correlation is significant at the 0.01 level (2-tailed).*

From the table above we can conclude that, samples beliefs on security and ethics of AI and Automation are highly correlated with beliefs on Organizational sustainability ($r=0.696$, $p<0.000$), social and ethical impacts ($r=0.314$, $p=0.000<0.05$), Strategic integration ($r=0.302$, $p=0.001<0.05$) and Impact on Human Resources and the Future of Work ($r=0.587$, $p=0.000<0.05$). All the correlations above are statistically significant and their strength varies between strong and mild linear correlations. On the other hand, beliefs on organizational sustainability seem to be correlated with strategic innovation ($r=0.373$, $p=0.000<0.05$) and Impact on Human Resources and the Future of Work ($r=0.672$, $p=0.000<0.05$). Lastly beliefs in strategic Integration are statistically significantly correlated with beliefs on Impact on Human Resources and the Future of Work ($r=0.371$, $p=0.000<0.05$).

In order to assess the main areas that influence samples attitudes and beliefs towards AI and automation, exploratory factor analysis was implemented with the method of

Principal Components and Varimax Rotation. From the Kaiser- Meyer – Olkin Measure for sample adequacy (KMO=0.857) we can conclude that data are correlated and suitable for analysis, while Bartlett's test of Sphericity (x^2=2244.122, DF=528, p=0.000<0.05) we can conclude that the Sphericity criterion is matched.

Principal Component Analysis (PCA) was conducted to identify underlying dimensions within the questionnaire data. The analysis extracted eight distinct factors, which together account for 68.40% of the total variance in participants' responses. This indicates a strong representation of the data structure and suggests that these eight components effectively capture the key themes influencing attitudes toward AI and automation. The distribution of variance explained by each component is illustrated in the scree plot below:

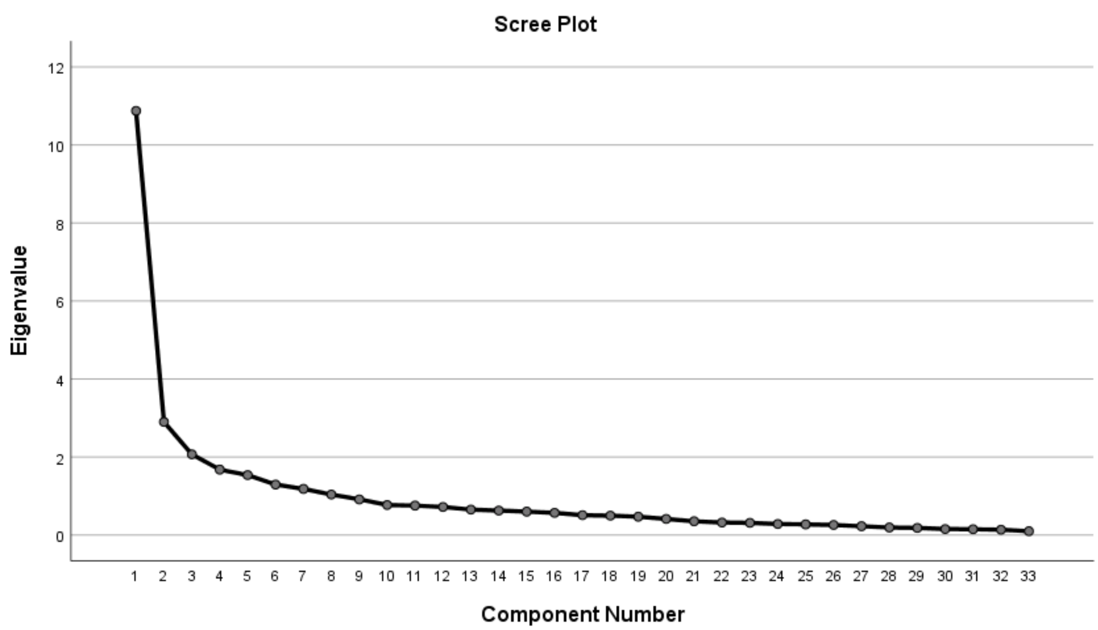

Table 17 presents the eight factors extracted through PCA, along with their associated components and factor loadings following Varimax rotation. The components are listed in ascending order based on their factor loadings, allowing for a clearer interpretation of the strength and alignment of each variable within its corresponding factor.

Table 27: Extracted Components and factor Loadings

Item	Loading
Factor 1: Dynamics of AI and Automation	
AI systems and automation tools enhance productivity and help achieve strategic goals.	0.802
AI and automation allow us to scale operations while maintaining quality standards.	0.772
AI-driven automation enables faster adaptation to market changes and external challenges, strengthening organizational resilience.	0.716
AI fosters innovation and helps organizations develop competitive advantages.	0.701
The use of AI supports long-term business sustainability and growth.	0.675
AI-driven automation improves efficiency by eliminating repetitive and time-consuming tasks.	0.673
Organizational sustainability is about equipping organizations with the people and structures necessary for success in the global marketplace of the 21st century.	0.620
AI and automation reduce human error and improve the accuracy of workplace processes.	0.531
Information systems and AI-related technologies are essential skills for the future workforce.	0.522
Specializing in automation and AI technologies now seems like a promising career choice.	0.497
Factor 2: AI and Automation in Work-place environment	
AI fosters creativity and innovation in workplace teams.	0.790
AI and automation help create new roles requiring advanced technical skills.	0.722
AI enhances training and development opportunities for employees.	0.707
AI and automation enhance the ability of humans to focus on creative and strategic tasks.	0.688
AI and automation can complement human work rather than replace it.	0.597
AI and automation allow for greater flexibility in workforce management.	0.592

AI and automation make my tasks more flexible and manageable.	0.508
Factor 3: AI and Automation Implementation in Organizations	
My organization has a clear and well-communicated strategy for integrating AI and automation.	0.872
My organization has a clear regulatory framework for the ethical implementation of AI and automation technologies.	0.863
My organization takes proactive measures to ensure inclusivity and fairness in the adoption of AI-driven technologies.	0.845
I am confident that my organization prioritizes ethics in AI and automation decisions.	0.579
Factor 4: Reliability, transparency and security of AI and Automation	
AI systems are more reliable than human verification for certain tasks.	0.805
AI and automation increase transparency in organizational decision-making and operations.	0.657
Automated and AI-supported data checks enhance security and minimize risks such as fraud.	0.560
Factor 5: Regulation and adaptation of AI and Automation	
I believe AI and automation should be regulated by external authorities or governments.	0.753
I feel supported in adapting to AI and automation in my role.	0.471
Factor 6: Challenges of AI and Automation	
The biggest challenge in adopting AI and automation in my organization is resistance to change.	0.747
The biggest challenge in adopting AI and automation in my organization is lack of skills among employees.	0.745
The biggest challenge in adopting AI and automation in my organization is high implementation costs.	0.548
Factor 7: Employees attitudes towards AI and Automation	
Employees are well-prepared for changes brought by AI and automation.	0.760
I feel confident in adapting to the changes brought by AI and automation.	0.545

Factor 8: Stress and workforce inequalities due to AI and Automation Implementation	
AI and automation increase stress and complexity in some roles.	0.729
AI and automation can lead to workforce inequalities.	0.665

The Table 17 indicates that participants' beliefs and attitudes toward AI and automation are influenced by several key factors: the dynamics of AI and automation, their presence in workplace environments, organizational implementation strategies, issues of reliability, transparency, and security, regulatory and adaptation mechanisms, perceived challenges, employee attitudes, and concerns related to stress and workforce inequalities resulting from AI and automation deployment.

Chapter 4: SUMMARY AND CONCLUSION

4.1 Overall Conclusions

The findings of this study underscore the transformative influence of Artificial Intelligence (AI) and automation on the future of work. Multiple aspects of work including organizational sustainability, security and ethics, strategic integration, and human resource management-are being reshaped by these technologies. Analysis of the survey data revealed that AI and automation are widely perceived as tools that improve workplace efficiency by automating repetitive tasks and reducing human error. Additionally, participants indicated that AI-supported data checks enhance security and help mitigate risks such as fraud, aligning with existing literature (Vajjala, 2018; Xu & Duan, 2024).

However, while respondents recognized improvements in operational transparency due to AI, there was hesitancy to regard AI systems as more reliable than human judgment for specific tasks. Transparency in organizational decision-making is a recognized benefit (Marsden, 2017), yet skepticism remains about the complete replacement of human capabilities (Lodhi et al., 2018).

Participants believed that AI facilitates the achievement of strategic goals, scalability, innovation, and long-term business sustainability-confirming prior research which highlights AI's role in enhancing organizational performance and data-driven growth (Fu & Mishra, 2021; Ercik & Kardaş, 2024). Nevertheless, ethical considerations emerged as underdeveloped within organizations. Many respondents indicated the absence of a clearly communicated strategy or regulatory framework for the ethical deployment of AI, consistent with scholars calling for standardized governance (Ryu & Han, 2018; Bywater et al., 2019).

From a workforce perspective, the data showed that organizations only modestly support inclusivity and fairness in AI implementation. There is a perceived lack of representation, especially in the development of inclusive AI systems, echoing concerns about disproportionate impacts on marginalized groups (Fu & Mishra, 2021).

Respondents also highlighted the potential of AI to create new roles requiring technical skills, enhance employee training, and promote creativity. While the workforce was moderately confident in adapting to these changes, many felt underprepared indicating a skills gap that must be addressed through targeted development initiatives. This supports the view that AI is best conceptualized as an "enabling" technology, complementing rather than replacing human labor.

The main barriers to AI adoption were identified as a lack of employee skills and resistance to change, while high implementation costs were seen as less significant. Importantly, no statistically significant differences were found in attitudes across demographic variables, suggesting that perceptions of AI's impact are broadly consistent across gender, age, experience, education level, and organizational size.

Correlation analysis further showed that beliefs about the security and ethics of AI were strongly related to beliefs about organizational sustainability, strategic integration, and its impact on human resources. Factor analysis identified eight core dimensions influencing attitudes toward AI, including workplace dynamics, implementation strategies, ethical challenges, and workforce inequalities.

The integration of AI into the workplace is both inevitable and transformative. Navigating this shift requires proactive planning, ethical foresight, inclusive policy design, and a commitment to workforce reskilling and adaptability.

4.2 Managerial and Practical Implications

This study offers several actionable insights for managers and organizational leaders. First, the strategic integration of AI must go beyond productivity gains; it should also address human factors such as employee confidence, skill development, and ethical concerns. Leaders should implement comprehensive communication strategies that clarify how AI complements human roles rather than displace them.

The core insight is unmistakable: organizations that strategically invest in their workforce-not solely in technology-will be better positioned to thrive in the evolving landscape of work. Employees are actively seeking direction and development, presenting a critical opportunity for employers to assume a proactive leadership role.

Fostering a collaborative and future-oriented workforce not only enhances organizational resilience and performance but also cultivates a workplace culture in which individuals feel supported, empowered, and prepared to adapt to emerging challenges.

According to the McKinsey Global Institute, up to 800 million jobs could be displaced by 2030, particularly in manufacturing, retail, and logistics (Manyika et al., 2017)

To facilitate this transition, upskilling is critical. The World Economic Forum stresses the importance of analytical thinking, creativity, and technological fluency. Meanwhile, emotional intelligence and leadership are increasingly valued as automation handles more technical tasks.

To mitigate workforce resistance and skills mismatches, organizations should invest in upskilling and reskilling programs that align with emerging AI-related competencies. These efforts should be complemented by ethical AI governance policies that ensure fairness, transparency, and inclusivity in AI deployment.

Managers must foster an organizational culture that is both technologically progressive and ethically grounded. Emphasizing human-centric values-such as empathy, fairness, and collaboration-will help ensure that technological innovation leads to sustainable and inclusive growth.

4.3 Theoretical Implications

This research contributes to the growing body of knowledge on the implications of AI and automation in organizational contexts. It reinforces theoretical frameworks that conceptualize AI not as a substitute, but as a complement to human labor, enabling enhanced performance, creativity, and innovation.

The findings also emphasize the central role of ethical considerations in shaping employee attitudes toward AI. This underscores the need for future theory to incorporate ethical governance as a core component of AI adoption models. Moreover, the results validate the importance of viewing AI adoption through an interdisciplinary lens that incorporates perspectives from technology, management, ethics, and labor economics.

By identifying eight distinct factors influencing AI perceptions-ranging from security and transparency to workplace readiness and stress-the study supports the development of multi-dimensional models for evaluating AI implementation outcomes.

4.4 Limitations

While this study provides meaningful insights, several limitations must be acknowledged. First, the use of a convenience sample limits the generalizability of the findings. The demographic distribution may not represent the wider workforce or different cultural and geographic contexts.

Second, the data relies on self-reported perceptions, which are inherently subjective and may not always reflect actual organizational practices or employee behavior. Social desirability bias may have influenced responses.

Third, the analysis captures perceptions at a single point in time, thus limiting the ability to assess the long-term impacts of AI and automation on employment, organizational culture, or ethics.

Lastly, although exploratory factor analysis provided useful dimensions, confirmatory factor analysis (CFA) was not conducted, and the hypotheses-driven inferential models were underdeveloped, limiting the explanatory power of the results.

4.5 Future Research Agenda

Future research should aim to address the limitations of this study through the following avenues:

1. Expand Demographic and Geographic Scope: Conduct studies across diverse regions and industries to better understand how socio-economic and cultural variables influence AI-related perceptions.

2. Longitudinal Research: Examine how attitudes and organizational outcomes evolve over time, particularly as AI becomes more deeply embedded in workplace practices.

3. Investigate Job Displacement and Economic Inequality: Explore how AI adoption impacts employment patterns, wage structures, and access to opportunity, especially among low-skilled or marginalized workers.

4. Ethical Framework Development: Conduct empirical studies on the effectiveness of regulatory frameworks, internal ethics policies, and algorithmic accountability mechanisms.

5. Human-AI Collaboration: Examine how AI can be used to augment human creativity, judgment, and decision-making, particularly in fields that rely heavily on human intuition and social interaction.

By addressing these areas, future research can offer a deeper, more nuanced understanding of the complex and evolving role of AI in modern organizations.

BIBLIOGRAPHICAL REFERENCES

1. Accenture. (2022). Accenture's approach to reskilling: Building a future-ready workforce. Retrieved from https://www.accenture.com/us-en/about/company-index

2. Accenture. (2023). Accenture academy: Building skills for the digital age. https://www.accenture.com/us-en/services/talent-organization/learning-academy

3. Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. NBER Working Paper No. 24196. National Bureau of Economic Research.

4. Amazon. (2021). Upskilling 2025 Annual Report. Retrieved from https://assets.aboutamazon.com/80/a2/7e01e544475aaf15b4f8d5067cc6/amazon-upskilling-report-final.pdf

5. Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. OECD Social, Employment and Migration Working Papers, No. 189. OECD Publishing. https://www.oecd.org/en/publications/the-risk-of-automation-for-jobs-in-oecd-countries_5jlz9h56dvq7-en.html

6. Ball, K. (2010). Workplace surveillance: An overview. Labor History, 51(1), 87–106. https://doi.org/10.1080/00236561003654776

7. Barocas, S., & Selbst, A. D. (2016). Big data’s disparate impact. California Law Review, 104(3), 671–732. https://doi.org/10.15779/Z38BG31

8. Bathla, G., Bhadane, K., Singh, R. K., Kumar, R., Aluvalu, R., & Krishnamurthi, R. (2022). Autonomous vehicles and intelligent automation: Applications, challenges, and opportunities. Mobile Information Systems, 2022, Article 7632892. https://doi.org/10.1155/2022/7632892

9. Benanav, A. (2019). Automation and the future of work—Part 1. New Left Review, 119, 5–38.

10. Bessen, J. E. (2019). AI and jobs: The role of demand. NBER Working Paper No. 24235. National Bureau of Economic Research. https://www.nber.org/system/files/working_papers/w24235/w24235

11. Binns, R. (2018). Fairness in machine learning: Lessons from political philosophy. In S. A. Friedler & C. Wilson (Eds.), Proceedings of the 1st Conference on Fairness, Accountability and Transparency (pp. 149–159). PMLR. https://proceedings.mlr.press/v81/binns18a.html

12. Bletsas, A. (2023). AI, power, and the politics of technology. Journal of Technology and Society, 45(1), 101–118.

13. Bolarinwa, O. A. (2015). Principles and methods of validity and reliability testing of questionnaires used in social and health science researches. Nigerian Postgraduate Medical Journal, 22(4), 195–201. https://doi.org/10.4103/1117-1936.173959

14. Bostrom, N. (2014). Superintelligence: Paths, dangers, strategies. Oxford University Press.

15. Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.

16. Bryman, A. (2017). Quantitative and qualitative research: Further reflections on their integration. In Mixing methods: Qualitative and quantitative research (pp. 57–78). Routledge.

17. Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.

18. Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., & Trench, M. (2018). Skill shift: Automation and the future of the workforce. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce

19. Bywater, T., Smith, J., & Lee, A. (2019). Ethical frameworks in AI deployment. Journal of Artificial Intelligence Ethics, 12(3), 45–60.

20. Chalkiadaki, A. (2018). A systematic literature review of 21st century skills and competencies in primary education. International Journal of Instruction, 11(3), 1–16. https://doi.org/10.12973/iji.2018.1131a

21. Chui, M., Manyika, J., & Miremadi, M. (2018). What AI can and can't do (yet) for your business. McKinsey Quarterly. Retrieved from https://www.mckinsey.com/featured-insights/artificial-intelligence/what-ai-can-and-cant-do-yet-for-your-business

22. Chui, M., Manyika, J., & Miremadi, M. (2018). Notes from the AI frontier: Applications and value of deep learning. McKinsey & Company

23. Crawford, K. (2021). Atlas of AI: Power, politics, and the planetary costs of artificial intelligence. Yale University Press.

24. Choi, T. M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, 27(10), 1868–1883. https://doi.org/10.1111/poms.12838

25. Carbonero, F., Ernst, E., & Weber, E. (2020). Robots worldwide: The impact of automation on employment and trade (IAB Discussion Paper No. 07/2020). Institute for Employment Research (IAB). https://doku.iab.de/discussionpapers/2020/dp0720.pdf

26. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

27. Creswell, J. W., & Poth, C. N. (2016). Qualitative inquiry and research design: Choosing among five approaches (4th ed.). SAGE Publications.

28. Dastin, J. (2018, October 10). Amazon scraps secret AI recruiting tool that showed bias against women. Reuters. Retrieved from https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G

29. Deloitte. (2023). 2023 Global Human Capital Trends. Deloitte Insights. https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2023.html

30. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

31. Davenport, T. H., Guha, A., Grewal, D., & Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48(1), 24–42. https://doi.org/10.1007/s11747-019-00696-0

32. Divya, D., Jain, R., Chetty, P., Siwach, V., & Mathur, A. (2024). The mediating effect of leadership in artificial intelligence success for employee engagement. Management Decision, Advance online publication. https://doi.org/10.1108/MD-01-2024-0213

33. European Parliament. (2018). A definition of artificial intelligence: Main capabilities and scientific disciplines. https://www.europarl.europa.eu/RegData/etudes/STUD/2018/614547/EPRS_STU(2018)614547_EN.pdf

34. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115–118. https://doi.org/10.1038/nature21056

35. Ercik, M., & Kardaş, S. (2024). AI integration and organizational performance. International Journal of Business Technology, 29(1), 112–130.

36. Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American Journal of Theoretical and Applied Statistics, 5(1), 1–4. https://doi.org/10.11648/j.ajtas.20160501.11

37. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schäfer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

38. Field, A. (2013). Discovering statistics using IBM SPSS Statistics (4th ed.). SAGE Publications.

39. Fu, H., & Mishra, R. (2021). Strategic integration of AI in business operations. Business Innovation Quarterly, 15(2), 78–95.

40. Gunderson Dettmer. (2024). 2024 Generative AI Future of Work Survey Report. Retrieved from https://www.gunder.com/en/news-insights/insights/gunderson-dettmer-releases-2024-generative-ai-future-of-work-survey-report

41. Gómez-Uribe, C. A., & Hunt, N. (2015). The Netflix recommender system: Algorithms, business value, and innovation. ACM Transactions on Management Information Systems, 6(4), Article 13. https://doi.org/10.1145/2843948

42. Goswami, S., & Mondal, S. (2025). Stochastic Models for Autonomous Systems and Robotics. Spectrum of Operational Research. 3. 215-237. https://doi.org/10.31181/sor31202647

43. Ghahramani, A., Tang, C., & Becerik-Gerber, B. (2020). An Artificial Intelligence-Based Occupant-Centric Framework for Sustainable Smart Buildings. Journal: Frontiers in Built Environment, 6, Article 49. https://doi.org/10.3389/fbuil.2020.00049

44. Gharaibeh, A., Salahuddin, M., Hussini, S. J., Khreishah, A., Khalil, I., Guizani, M., & Al-Fuqaha, A. (2017). Smart cities: A survey on data management, security, and enabling technologies. IEEE Communications Surveys & Tutorials, 19(4), 2456–2501. https://doi.org/10.1109/COMST.2017.2736886

45. Gulshan, V., Peng, L., Coram, M., Stumpe, M. C., Wu, D., Narayanaswamy, A.,& Webster, D. R. (2016). Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA, 316(22), 2402–2410. https://doi.org/10.1001/jama.2016.17216

46. Holstein, K., McLaren, B. M., & Aleven, V. (2019). Designing for complementarity: Teacher and student needs for orchestration support in AI-enhanced classrooms. In S. Isotani, E. Millán, A. Ogan, P. Hastings, B. McLaren, & R. Luckin (Eds.), Artificial Intelligence in Education (pp. 157–171). Springer. https://doi.org/10.1007/978-3-030-23204-7_14

47. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Pearson Education.

48. Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. Evidence-Based Nursing, 18(3), 66–67. https://doi.org/10.1136/eb-2015-102129

49. IBM. (2021). IBM SkillsBuild: Empowering the workforce of the future.

50. IBM Institute for Business Value. (2023, October). *CEO decision-making in the age of AI: Act with intention* (Executive Report). https://www.ibm.com/thought-leadership/institute-business-value/en-us/report/ceo-generative-ai/ceo-ai-finance

51. IBM. (2024). Upskilling and reskilling for talent transformation in the era of AI. Retrieved from https://www.ibm.com/think/insights/ai-upskilling

52. Jovovic Vucinic, Milena & Luburić, Radoica. (2024). Artificial Intelligence, Fintech and Challenges to Central Banks. Journal of Central Banking Theory and Practice, 13, 5-42. https://doi.org/10.2478/jcbtp-2024-0021

53. Joshi, S. (2025). Generative AI: Mitigating workforce and economic disruptions while strategizing policy responses for governments and companies. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5135229

54. Lacity, M., & Willcocks, L. (2015). Robotic process automation at Telefónica O2. The Outsourcing Unit Working Research Paper Series, London School of Economics and Political Science.

55. Lane, M. and A. Saint-Martin (2021). The impact of Artificial Intelligence on the labour market: What do we know so far? OECD Social, Employment and Migration Working Papers, No. 256, OECD Publishing, Paris. https://doi.org/10.1787/7c895724-en

56. Lam, A. Y. S. (2025). Artificial Intelligence Applications in Financial Technology. Journal of Theoretical and Applied Electronic Commerce Research, 20(1), 29. https://doi.org/10.3390/jtaer20010029

57. Lee, J., Bagheri, B., & Kao, H.-A. (2014). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23.

58. Lin, P. (2020). Why ethics matters for autonomous cars. In M. Maurer, J. C. Gerdes, B. Lenz, & H. Winner (Eds.), Autonomous driving (pp. 69–85). Springer. https://doi.org/10.1007/978-3-662-48847-8_4

59. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence unleashed: An argument for AI in education. Pearson Education.

60. Lodhi, F., Ahmed, S., & Khan, R. (2018). Human judgment versus AI systems: A comparative study. Journal of Cognitive Computing, 10(4), 210–225.

61. Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., & Sanghvi, S. (2017). Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages. McKinsey Global Institute. https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages

62. Marsden, C. (2017). Transparency in AI decision-making processes. AI & Society, 32(3), 305–315.

63. Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. Nature Machine Intelligence, 1(11), 501–507.

64. Mucci, T., & Stryker, C. (2023, December 18). What is artificial superintelligence? IBM. https://www.ibm.com/think/topics/artificial-superintelligence

65. Microsoft. (2022). Microsoft global skills initiative: Bridging the digital skills gap. https://news.microsoft.com/skills/

66. Manyika, J., Silberg, J., & Presten, B. (2017). What do we do about the biases in AI? Harvard Business Review.

67. McKinsey & Company. (2024). The state of AI in 2024: Generative AI's breakout year. McKinsey & Company.

68. Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2). https://doi.org/10.1177/2053951716679679

69. Müller, H., & Sidki, M. (2025).Artificial intelligence as a tool to evaluate corporate sustainability reporting. In C. R. Tănăsescu, C. Oprean-Stan, S. O. Idowu, & B. Díaz Díaz (Eds.), Advancements in sustainable development (pp. 71–83). Springer. https://doi.org/10.1007/978-3-031-86337-0_5

70. Neuman, W. L. (2014). Social research methods: Qualitative and quantitative approaches (7th ed.). Pearson Education Limited.

71. Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

72. Nguyen, Thanh. (2020). Artificial Intelligence in the Battle against Coronavirus (COVID-19): A Survey and Future Research Directions. https://doi.org/10.13140/RG.2.2.36491.23846/1

73. OECD. (2019). *The Future of Work: OECD Employment Outlook 2019*. OECD Publishing. https://doi.org/10.1787/9ee00155-en

74. OpenAI. (2023). *GPT-4 technical report*. https://openai.com/research/gpt-4

75. Pagallo, U. (2013). The laws of robots: Crimes, contracts, and torts. Springer. https://doi.org/10.1007/978-94-007-6564-1

76. Rabianski, J. S. (2003). Primary and secondary data: Concepts, concerns, errors, and issues. The Appraisal Journal, 71(1), 43–55.

77. Robson, C. (2011). Real world research: A resource for users of social research methods in applied settings (3rd ed.). Wiley.

78. Ryu, M., & Han, C. (2018). Standardizing AI governance in organizations. Journal of Technology Ethics, 9(1), 50–65.

79. Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 469–481. https://doi.org/10.1145/3351095.3372828

80. Raisch, S., & Krakowski, S. (2020). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072

81. Rajesh, S., Kandaswamy, U., & Rakesh, A. (2018). The impact of artificial intelligence in talent acquisition lifecycle of organizations: A global perspective. International Journal of Engineering Development and Research, 6(2), 709–717.

82. Russell, S., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

83. Raisch, S., & Krakowski, S. (2020). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 45(1), 90–107. https://doi.org/10.5465/amr.2018.0072

84. Saunders, M., Lewis, P., & Thornhill, A. (2012). Research methods for business students (6th ed.). Pearson Education Limited.

85. Setia, M. S. (2016). Methodology series module 3: Cross-sectional studies. Indian Journal of Dermatology, 61(3), 261–264. https://doi.org/10.4103/0019-5154.182410

86. Shin, D. (2020). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human–Computer Studies*, 146, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

87. Salesforce. (2022). Trailhead: The fun way to learn. https://trailhead.salesforce.com/

88. SkillsFuture Singapore. (n.d.). SkillsFuture. https://www.skillsfuture.gov.sg/

89. Sparrow, R., & Sparrow, L. (2006). In the hands of machines? The future of aged care. Minds and Machines, 16(2), 141–161. https://doi.org/10.1007/s11023-006-9030-6

90. Shollo, A., & Galliers, R. D. (2016). Towards an understanding of the role of business intelligence systems in organisational knowing. Information Systems Journal, 26(4), 339–367. https://doi.org/10.1111/isj.12071

91. Sartori, L., & Theodorou, A. (2022). A sociotechnical perspective for the future of AI: Narratives, inequalities, and human control. Ethics and Information Technology, 24, Article 24. https://doi.org/10.1007/s10676-022-09624-3

92. Siderska, J. (2020). Robotic Process Automation—a driver of digital transformation? Engineering Management in Production and Services, 12(1), 21–31. https://doi.org/10.2478/emj-2020-0009

93. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

94. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910

95. Tarus, J. K., Gichoya, D., & Muumbo, A. (2018). Challenges of implementing e-learning in Kenya: A case of Kenyan public universities. International Review of Research in Open and Distributed Learning, 16(1), 120–141. https://doi.org/10.19173/irrodl.v16i1.1816

96. Tesla. (n.d.). *Autopilot and full self-driving capability*. https://www.tesla.com/autopilot

97. Turing, A. M. (1950). Computing machinery and intelligence. Mind, 59(236), 433–460. https://doi.org/10.1093/mind/LIX.236.433

98. Tuyen, Nguyen. (2025). The Impact of Transformational Leadership on Knowledge Acquisition and Transfer: The Mediating Roles of Employee Engagement and Autonomy. International

99. Vajjala, S. (2018). Automated assessment of non-native learner essays: Investigating the role of linguistic features. In Proceedings of the Thirteenth Workshop on Innovative Use of NLP for Building Educational Applications (pp. 169–179). Association for Computational Linguistics. https://aclanthology.org/W18-0517/

100. Willcocks, L., Lacity, M., & Craig, A. (2015). The IT function and Robotic Process Automation. The Outsourcing Unit Working Research Paper Series, London School of Economics.

101. Westerman, G., Bonnet, D., & McAfee, A. (2014). Leading digital: Turning technology into business transformation. Harvard Business Review Press.

102. World Economic Forum. (2023). The future of jobs report 2023. https://www.weforum.org/reports/the-future-of-jobs-report-2023

103. West, S. M., Whittaker, M., & Crawford, K. (2019). Discriminating systems: Gender, race and power in AI. AI Now Institute. https://ainowinstitute.org/wp-content/uploads/2023/04/discriminatingsystems.pdf

104. Whittlestone, J., Nyrup, R., Alexandrova, A., & Cave, S. (2019). The role and limits of principles in AI ethics: Towards a focus on tensions. In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (pp. 195–200). ACM. https://doi.org/10.1145/3306618.3314289

105. World Economic Forum. (2025, January). Future-ready workers and investing in people. https://www.weforum.org/stories/2025/01/future-ready-workers-and-investing-in-people/

106. Xu, H., & Duan, R. (2024). AI-supported data checks and workplace security. Journal of Information Security, 18(2), 134–150.

107. Yampolskiy, R. V. (2015). Artificial superintelligence: A futuristic approach. CRC Press. https://doi.org/10.1201/b18612

108. Yildirim, N., Richardson, H., Wetscherek, M. T., Bajwa, J., Jacob, J., Pinnock, M. A., Harris, S., Coelho de Castro, D., Bannur, S., Hyland, S. L., Ghosh, P., Ranjit,

M., Bouzid, K., Schwaighofer, A., Pérez-García, F., Sharma, H., Oktay, O., Lungren, M. P., Alvarez-Valle, J., Nori, A., & Thieme, A. (2024). Multimodal healthcare AI: Identifying and designing clinically relevant vision-language applications for radiology. In Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (pp. 1–22). ACM. https://doi.org/10.1145/3613904.3642013

109. Yang, G., Zhang, H., Wang, J., & Zhang, Y. (2020). Autonomous robotic surgery: Has the future arrived? Frontiers in Robotics and AI, 7, 1–10. https://doi.org/10.3389/frobt.2020.00001

110. Zuboff, S. (2019). The age of surveillance capitalism: The fight for a human future at the new frontier of power. PublicAffairs.

ANNEX

Questionnaire

Dear Participant,

This study investigates the impact of automation and artificial intelligence (AI) on the future of work, with a focus on their strategic integration within organizations. The research aims to understand how these technologies influence employees, managers, and organizations, particularly in terms of changes in job roles, required skill sets, human-technology collaboration, and ethical and social considerations. Additionally, it examines strategies for effectively leveraging AI and automation to ensure sustainability and equity in the workplace.

The study is conducted by Sofia Kali, an M.Sc. student in the Master in Technology and Innovation Management. Your valuable contribution to my final thesis, titled *"Impact of Automation and AI in the Future of Work: A Strategic Perspective,"* is greatly appreciated. This questionnaire plays a critical role in collecting data, and your participation is essential. Please remember that there are no right or wrong answers-simply select the options that best reflect your knowledge and beliefs.

Your responses will remain anonymous and will only be used for academic purposes. The data collected will be presented in aggregated form to ensure confidentiality. While participating in this research does not provide any personal benefit, your input will contribute to further understanding and knowledge in this important area.

Estimated time to complete the questionnaire: 5 minutes.

By participating in this research, you confirm that you have read this information and agree to take part in the study.

Thank you for your time and support.

Sincerely,

Section A. Demographics

1. Gender:

Woman

Man

Other

Prefer not to answer

2. Age level:

20 - 34

35 - 44

45 - 54

55 +

3. Studies:

High School/college graduate, diploma or equivalent

Bachelor's degree

Master's degree
Ph.D
Prefer not to say

4. Sector of activities of your company:

Agriculture/Food
Manufacturing
Construction
Energy
ICT
Financial Sector
Healthcare
Retail
Transportation and Logistics
Real Estate
Hospitality and Tourism
Education Sector
Government and Public Administration
Nonprofit and Social Services
Entertainment and Media
Consulting Services
Automotive Sector
Aerospace and Defense
Environmental and Green Energy
Pharmaceuticals and Biotechnology
Insurance
Legal Services

5. Closest representation to your role within the organization?

Executive/Managerial
Professional/Technical
Administrative/Support
Sales/Marketing
Operations/Production
Customer Service
IT/Computing
Human Resources
Finance/Accounting
Research and Development
Design
Education/Training
Healthcare
Legal
Public Relations/Communications
Other

6. Work experience:

Less than 1 year
1-5 years
6-10 years
More than 10 years

7. The company you work for has:

1 - 10 employees
11 - 50 employees
51- 250 employees
251+ employees

8. In the company you work for, artificial intelligence and automation are used in:

Customer support (e.g., chatbots, automated responses)

Operational workflows (e.g., AI-driven process automation, data analysis, roboti process automation)

Human resource management (e.g., recruitment, employee evaluati on, payroll)

Decision-making support (e.g., predictive analytics, dashboards)

Product or service development (e.g., AI-driven innovation, R&D)

Supply chain and logistics (e.g., inventory management, automated scheduling)

Not applicable – AI and automation are not currently used in my organization

Other tasks

I don't know / I don't answer

Section B. Artificial intelligence & Automation , levels of security and ethics

To what extent do you agree with the following?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
AI and automation reduce human error and improve the	1	2	3	4	5

accuracy of workplace processes.					
AI-driven automation improves efficiency by eliminating repetitive and time-consuming tasks.	1	2	3	4	5
Automated and AI-supported data checks enhance security and minimize risks such as fraud.	1	2	3	4	5
AI systems are more reliable than human verification for certain tasks.	1	2	3	4	5
AI and automation increase transparency in organizational decision-making and operations.	1	2	3	4	5
I feel supported in adapting to AI and automation in my role.	1	2	3	4	5
I am confident that my organization prioritizes ethics in AI and automation decisions.	1	2	3	4	5
My organization has a clear regulatory framework for the	1	2	3	4	5

ethical implementation of AI and automation technologies.					

Section C. AI and Automation in Organizational Sustainability

To what extent do you agree with the following?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
AI and automation reduce personnel costs and improve resource allocation.	1	2	3	4	5
AI systems and automation tools enhance productivity and help achieve strategic goals.	1	2	3	4	5
AI and automation allow us to scale operations while maintaining quality standards.	1	2	3	4	5
AI fosters innovation and helps organizations develop competitive advantages.	1	2	3	4	5
AI-driven automation enables faster adaptation to market changes and external challenges, strengthening organizational resilience.	1	2	3	4	5

The use of AI supports long-term business sustainability and growth.	1	2	3	4	5

Section D. Social and Ethical Impacts of AI and Automation

To what extent do you agree with the following?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
AI and automation can lead to workforce inequalities.	1	2	3	4	5
My organization takes proactive measures to ensure inclusivity and fairness in the adoption of AI-driven technologies.	1	2	3	4	5
I believe AI and automation should be regulated by external authorities or governments.	1	2	3	4	5

Section E. Strategic Integration of AI and Automation

To what extent do you agree with the following?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree

My organization has a clear and well-communicated strategy for integrating AI and automation.	1	2	3	4	5
The biggest challenge in adopting AI and automation in my organization is resistance to change.	1	2	3	4	5
The biggest challenge in adopting AI and automation in my organization is lack of skills among employees.	1	2	3	4	5
The biggest challenge in adopting AI and automation in my organization is high implementation costs.	1	2	3	4	5

Section F. AI and Automation's Impact on Human Resources and the Future of Work

To what extent do you agree with the following?

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly agree
AI and automation help create new roles requiring advanced technical skills.	1	2	3	4	5

AI enhances training and development opportunities for employees.	1	2	3	4	5
AI fosters creativity and innovation in workplace teams.	1	2	3	4	5
AI and automation enhance the ability of humans to focus on creative and strategic tasks.	1	2	3	4	5
AI and automation make my tasks more flexible and manageable.	1	2	3	4	5
AI and automation allow for greater flexibility in workforce management.	1	2	3	4	5
AI and automation increase stress and complexity in some roles.	1	2	3	4	5
I feel confident in adapting to the changes brought by AI and automation.	1	2	3	4	5
Employees are well-prepared for changes brought by AI and automation.	1	2	3	4	5
Information systems and AI-related technologies are essential skills for the future workforce.	1	2	3	4	5
Specializing in automation and	1	2	3	4	5

AI technologies now seems like a promising career choice.					
AI and automation can complement human work rather than replace it.	1	2	3	4	5