Intelligent Integration of Artificial Intelligence in Professional Training: A Case Study of Organizational Transformation in Tunisian Industry

Intégration intelligente de l'intelligence artificielle dans la formation professionnelle : étude de cas sur la transformation organisationnelle dans l'industrie tunisienne

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Abstract

This study examines the organizational conditions that enable successful integration of Artificial Intelligence (AI) within industrial enterprises in Tunisia. Using a qualitative case study approach, the research draws on seven semi-structured interviews conducted with managers and employees to explore perceptions of AI and its implications for workforce development. Thematic analysis of the interviews, following an iterative coding procedure, revealed three central themes.

Findings reveal a broadly positive view of AI, perceived as a catalyst for process optimization and productivity enhancement across key operational areas such as sales, production, and human resources. Crucially, the study underscores the principle of human–technology complementarity, where AI is framed not as a replacement for human labor but as a strategic support that augments human capabilities.

Continuous learning emerges as the cornerstone of effective AI adoption. The organization studied demonstrates a proactive, role-specific training strategy tailored to hierarchical levels, combining technical proficiency (e.g., tool mastery) with soft skills (e.g., communication, stress management). This dual-focus approach transforms technological disruption into an opportunity for organizational and individual growth.

Keywords: Artificial Intelligence, continuous learning, human–technology complementarity, industrial transformation, qualitative case study, Tunisia.

Résumé

Cette étude examine les conditions organisationnelles qui permettent une intégration réussie de l'Intelligence Artificielle (IA) au sein des entreprises industrielles en Tunisie. Adoptant une approche qualitative par étude de cas, la recherche s'appuie sur sept entretiens semi-directifs menés auprès de managers et d'employés pour explorer les perceptions de l'IA et ses implications pour le développement des compétences. L'analyse thématique des entretiens, suivant une procédure de codage itérative, a fait émerger trois thèmes centraux.

Les résultats révèlent une vision globalement positive de l'IA, perçue comme un catalyseur d'optimisation des processus et d'amélioration de la productivité dans des domaines opérationnels clés tels que les ventes, la production et les ressources humaines. Surtout, l'étude souligne le principe de complémentarité humain-technologie, où l'IA n'est pas envisagée comme un remplacement de la main-d'œuvre humaine mais comme un soutien stratégique qui augmente les capacités humaines.

L'apprentissage continu émerge comme la pierre angulaire d'une adoption efficace de l'IA. L'organisation étudiée démontre une stratégie de formation proactive et spécifique aux rôles, adaptée aux niveaux hiérarchiques, combinant la maîtrise technique (ex. : maîtrise des outils) et les compétences douces (ex. : communication, gestion du stress). Cette approche à double focalisation transforme la disruption technologique en une opportunité de croissance organisationnelle et individuelle.

Mots-clés: Intelligence Artificielle, apprentissage continu, complémentarité humain-technologie, transformation industrielle, étude de cas qualitative, Tunisie.

Introduction

The introduction of emerging technologies—particularly Artificial Intelligence (AI)—requires organizations to implement robust and continuous training systems (Billiot, 2023). Regardless of size or sector, training has become a strategic cornerstone for organizational success. For employees, it offers the opportunity to become more competent, creative, responsible, and autonomous, while also enhancing their ability to make informed decisions (Soegiarto et al., 2024; Sadewa & Ridwan, 2024). Ultimately, this investment in human capital aims to improve both productivity and performance. Continuous training also leads to a redefinition of employee responsibilities and fosters new collective dynamics within the workplace. It is essential for maintaining strategic competitiveness in an increasingly digital environment (Korzovatykh et al., 2021). More than ever, AI represents a powerful lever for organizational development and survival. In this context, employees must be equipped—through targeted training—to master these technologies and align with the organization's strategic vision (Sposato, 2024). As Berton (1990) emphasized, training enables companies to prepare for technological change, avoid layoffs, and address work-related challenges.

The integration of AI, viewed through the lens of human–machine complementarity (Wilson & Daugherty, 2018), places continuous training at the heart of developing the organization's dynamic capabilities, particularly its absorptive capacity (Cohen & Levinthal, 1990).

Training is thus defined as a managerial process primarily aimed at adapting employees to the evolving needs of the organization (Gaha, 2010). Over time, organizations have come to recognize its critical role in helping employees attain higher levels of knowledge, expertise, and skill. It is now widely regarded as a strategic investment to enhance productivity, efficiency, and competitiveness (Mustafa & Lleshi, 2024). Companies must continuously develop the capabilities of their workforce, and ongoing training facilitates the mastery of new tasks and technologies. By allocating dedicated resources to training, organizations improve employee performance and more effectively achieve their objectives (Gaha, 2010).

Moreover, training guides employees in adapting to new digital tools and systems, serving as a vital support mechanism (Rustam, 2024). As Dragomir (2010) notes, the higher the percentage of trained employees, the greater the overall competency level of the organization. In this regard, training is a central concern for all personnel, valued for its ability to empower individuals and strengthen organizational efficiency and resilience.

The integration of emerging technologies—particularly Artificial Intelligence (AI)—has become a strategic imperative for organizations seeking to enhance competitiveness, agility, and innovation . Across industries and regions, AI is reshaping operational models, redefining job roles, and challenging traditional approaches to workforce development. In this evolving landscape, continuous training has emerged as a critical enabler, allowing employees to adapt to technological change, acquire new competencies, and contribute meaningfully to organizational transformation (Rustam, 2024).

Training is no longer a peripheral function; it is a central pillar of strategic management. For employees, it fosters autonomy, creativity, and decision-making capacity. For organizations, it represents an investment in human capital aimed at improving productivity, performance, and resilience (Becker, 2002). As AI technologies become more embedded in business processes, the need for targeted, ongoing training intensifies—particularly in areas such as human–machine collaboration, digital literacy, and adaptive soft skills. Scholars have emphasized that AI should not be viewed merely as a tool for automation, but as a complement to human capabilities requiring new forms of organizational learning and support (Berton, 1990; Gaha, 2010; Dragomir, 2010).

While the literature offers extensive insights into AI adoption and workforce training as separate domains, their synergistic relationship remains underexplored—particularly within industrial firms in emerging economies. In Tunisia, this intersection is both theoretically and empirically overlooked. Few studies have examined how continuous training mediates AI integration or how employees perceive and respond to these transformations within local organizational cultures.

This study therefore seeks to address this gap through an exploratory case study of the Tunisian industrial enterprise SOPAL. It investigates how AI-related training influences employee motivation, skill development, and organizational performance. Specifically, it explores how training functions as a strategic lever for successful AI integration by examining its impact on evolving job roles, competencies, and organizational structures, as well as its perceived effects on employee autonomy, motivation, and sense of value.

To guide this inquiry, the study poses the following central research question: *To what extent is employee training a strategic lever for the successful integration of Artificial Intelligence within Tunisian industrial organizations, and what are its effects on the evolution of skills, organizational structures, and employee perceptions?*

To answer this question, a qualitative approach was adopted through an in-depth case study of SOPAL. Data were collected via seven semi-structured interviews with managers and employees, providing rich, contextualized insights into the role of training in AI adoption.

The remainder of this paper is organized as follows: Section 2 reviews the theoretical framework linking AI integration and organizational transformation, emphasizing the strategic role of continuous training. Section 3 presents the research methodology and empirical findings from SOPAL. Finally, Section 4 discusses the theoretical and managerial implications of these findings and offers directions for future research.

1. Literrature Review

Artificial Intelligence (AI) has rapidly evolved from a niche technological innovation to a central pillar of organizational strategy, fundamentally altering the way firms operate, compete, and manage their human capital (Sposato,2024). Initially confined to experimental applications, AI now permeates core business functions—from operations and marketing to finance and human resources—ushering in a new era of data-driven decision-making and intelligent automation (Shmatko & Ivchyk , 2024) .Its integration into organizational processes transcends mere efficiency gains; it signals a paradigmatic shift in how organizations conceptualize value creation, strategic agility, and sustainable performance.

Beyond technological disruption, AI drives profound changes in work design and employee capability requirements, thereby positioning continuous training as a strategic necessity rather than an operational support function. AI challenges traditional boundaries between human cognition and machine computation, fostering hybrid intelligence systems that combine algorithmic precision with human judgment (Inkpen et al., 2023). This convergence enables novel forms of collaboration, distributed decision-making, and adaptive organizational design (Serge, 2018). As intelligent systems increasingly participate in tasks once reserved for humans—such as forecasting, diagnostics, and strategic planning—managers are compelled to rethink the nature of work, the structure of teams, and the competencies required for success in digitally augmented environments.

Moreover, AI is not only a technological disruptor but a socio-organizational catalyst. It redefines leadership roles, reshapes employee expectations, and introduces new ethical and governance challenges. The rise of algorithmic management, predictive HR analytics, and autonomous systems demands a reconfiguration of managerial paradigms, emphasizing agility, transparency, and continuous learning (Sposato,2024).
In this sense, AI compels organizations to strengthen their learning ecosystems and invest in adaptive training systems capable of supporting both digital transformation and ethical accountability.
AI is increasingly viewed not just as a tool, but as a strategic resource that transforms organizational capabilities and necessitates a profound rethinking of workforce development, talent strategies, and organizational learning ecosystems .

1.1 Artificial Intelligence: Evolution and Progressive Integration

Artificial Intelligence (AI) has undergone a remarkable evolution over the past few decades, transitioning from a theoretical concept to an operational reality that is now indispensable in the business landscape. Its progressive integration has been driven by a convergence of several major technological advances.

First, improvements in computing infrastructure and the development of new machine learning methods have made AI both more powerful and adaptable to increasingly complex tasks, significantly enhancing operational efficiency across organizations .

Second, the rise of Big Data has played a pivotal role in this transformation. The ability to collect, store, and process massive volumes of data has provided AI systems with the “fuel” needed to refine their algorithms, achieving unprecedented accuracy in prediction and decision-support domains (Noel, 2018).

Third, successive breakthroughs in computing power—from the advent of personal computers in the 1980s and 1990s to today’s high-performance servers—have enabled the execution of complex AI algorithms. This evolution, exemplified by machines’ growing capacity to evaluate millions of positions per second, has been a critical technical prerequisite for AI’s emergence.

The confluence of these factors has facilitated the widespread adoption of AI, which now stands as a strategic tool for organizations seeking to optimize processes, drive innovation, and strengthen competitiveness in a globalized market.

1.2 The Technological Pillars of Contemporary AI

Artificial Intelligence is underpinned by several essential technological components that determine its performance and integration across various domains. Noel (2018) identifies four foundational elements that structure modern AI:

First, data serves as the raw material of AI. It plays a central role in machine learning, where the quality of data—in terms of consistency and diversity—directly influences the accuracy and effectiveness of intelligent systems. To ensure reliable analysis and prediction, the digitization process (data collection, storage, and processing) must be optimized. In this regard, Ganascia (2015, cited in Noel, 2018, p.19) notes that the volume of data exchanged on the Internet was approximately 500,000 times the holdings of the Bibliothèque nationale de France, illustrating the massive proliferation of exploitable data.

Second, technological tools are fundamental to the development of AI applications, particularly in areas such as speech recognition, machine translation, and expert systems. Thanks to algorithmic advances, these tools convert raw data into actionable insights, enabling forecasting and guiding strategic decisions (Son et al., 2023).

Third, AI techniques rely on sophisticated methods such as machine learning, deep learning, and rule-based engines. The evolution of modern computing has significantly improved the economic viability of AI, making its implementation more accessible and efficient for both businesses and researchers.

Finally, AI solutions encompass a wide range of practical applications, from autonomous vehicles and intelligent robots to customer segmentation tools and personalized recommendation systems (Garikapati & Shetiya, 2024; Bathla et al., 2022). These innovations demonstrate AI's capacity to replicate human cognitive functions, including contextual understanding, logical reasoning, autonomous learning, and complex problem-solving.

Thus, AI emerges as a critical technological lever, whose development is driven by the synergy between data, tools, techniques, and solutions. Its ongoing evolution is reshaping industrial and societal practices, contributing to a profound transformation of work modalities and decision-making processes (Makridakis, 2017).

For the purposes of this study, AI is defined by its organizational applications that involve a degree of decision-making autonomy and learning capability, such as predictive analytics for quality control or maintenance. We also include advanced automation technologies (RPA), which—though not considered "strong AI"—serve as a common entry point and significantly alter employees' work experiences.

1.3.AI and Organizational Transformation

Artificial Intelligence (AI) has evolved into a strategic cornerstone of organizational transformation, redefining how firms structure work, manage talent, and pursue innovation (Aakula et al., 2024). No longer confined to operational automation, AI now permeates decision-making processes, customer engagement strategies, and organizational learning systems. Its integration reflects a shift from mechanistic efficiency toward intelligent adaptability—where data-driven systems support dynamic responses to complex and uncertain environments (Dwivedi et al., 2021).

AI supports organizational ambidexterity (Tushman & O'Reilly, 1996) by enabling more efficient exploitation of existing processes through automation, while simultaneously fostering exploration of new opportunities via large-scale data analytics. This dual imperative places employee training at the core of organizational transformation.

In contemporary organizations, AI enables predictive analytics, real-time optimization, and personalized service delivery, fostering agility and strategic foresight (Jarrahi, 2018). These capabilities are particularly valuable in volatile markets, where firms must simultaneously exploit existing competencies and explore emergent opportunities—a duality known as organizational ambidexterity (Tushman and O’Reilly 1996).

Structurally, AI transforms traditional hierarchies by decentralizing authority and embedding intelligence into digital platforms .This shift supports flatter organizations, algorithmic coordination, and hybrid work models, which require new leadership paradigms grounded in digital fluency, ethical governance, and systems thinking (Baumann & Wu, 2023). Managers must now navigate the interplay between human judgment and algorithmic logic, balancing efficiency with accountability.

At the individual level, AI reconfigures job roles and skill requirements, challenging employees to adapt to augmented tasks and evolving expectations around autonomy, creativity, and decision-making (Rawashdeh, 2025). This transformation alters the psychological contract between employer and employee, demanding renewed attention to organizational culture, change management, and inclusive learning environments.

Moreover, the integration of artificial intelligence (AI) raises critical questions about fairness, transparency, and trust. As intelligent systems increasingly influence hiring, performance evaluation, and career progression, organizations must ensure that AI deployment aligns with ethical standards and supports human dignity. Recent research has emphasized the need for robust ethical frameworks that promote accountability, inclusivity, and fairness in AI development .These frameworks are essential for mitigating algorithmic bias and ensuring that AI systems operate in ways that are socially acceptable and legally compliant (Choung et al., 2023). This calls for a strategic approach to workforce development—one that embeds continuous learning, digital literacy, and ethical awareness at the core of organizational design. AI is not merely a technological tool; it is a transformative force that reshapes the foundations of organizational competitiveness, resilience, and human capital development. Its intelligent integration requires a holistic rethinking of how organizations learn, lead, and evolve in the age of digital augmentation.

1.4 Continuous Training as a Strategic Response

As Artificial Intelligence (AI) continues to reshape the workplace, continuous training has become a foundational element of organizational renewal. The rapid pace of technological evolution requires employees to regularly update their skills to remain effective, agile, and aligned with shifting strategic priorities (Babashahi et al., 2024). In this context, training is not simply a support mechanism—it is a transformative driver that enables organizations to build the human capabilities necessary to operate intelligent systems and navigate digital workflows. As artificial intelligence reshapes organizational processes, several scholars emphasize that workforce development must evolve to include adaptive learning, digital literacy, and human–machine collaboration (Babashahi et al., 2024). Training initiatives that focus on cognitive flexibility, ethical awareness, and technical proficiency are essential to ensure that employees can meaningfully engage with intelligent systems and contribute to digitally augmented environments.

Continuous training functions as a key resource within the Job Demands–Resources model (Bakker & Demerouti, 2017). By equipping employees to interact effectively with AI, it mitigates the demands associated with technological complexity and enhances motivation—ultimately leading to improved performance and greater well-being, as our findings will illustrate.

Recent research highlights the multifaceted role of training in enhancing organizational adaptability. It strengthens technical proficiency, cultivates soft skills, and fosters higher-order competencies such as digital literacy, critical thinking, and collaborative problem-solving (Donovan et al., 2015; Yusuf et al.,2024). These capabilities are essential in AI-augmented environments, where employees must interpret algorithmic outputs, interact with intelligent interfaces, and make informed decisions in complex, data-intensive contexts.

Training also plays a central role in organizational learning and innovation. It enables firms to absorb external knowledge, adapt best practices, and build absorptive capacity—the ability to recognize, assimilate, and apply new information (Cohen & Levinthal, 1990). In AI-driven organizations, this capacity becomes a key enabler of responsiveness and innovation performance.

In terms of talent development, continuous training contributes to both attraction and retention. Organizations that offer robust learning ecosystems are better positioned to recruit skilled professionals and foster long-term employee engagement (Keding, 2021). This is particularly relevant in the context of AI, where skill obsolescence is rapid and the demand for interdisciplinary talent—combining technical, analytical, and human-centered competencies—is accelerating (Babashahi et al., 2024).

From a change management perspective, training helps mitigate resistance to technological disruption. It facilitates digital transformation by equipping employees to understand new tools, adapt to evolving roles, and remain engaged throughout innovation cycles (Dragomir, 2010; Berton, 1990). As AI continues to influence job design and organizational structures, structured upskilling becomes essential for maintaining workforce relevance and cohesion (Parween, 2024).

Equally important is the ethical dimension of training. In data-driven environments, employees must be prepared to question algorithmic decisions, identify biases, and uphold organizational values. Training thus becomes a vehicle for responsible AI deployment, supporting transparency, inclusion, and accountability (Autor et al., 2003).

Beyond traditional models, the rise of AI has accelerated a shift toward lifelong learning and flexible credentialing systems. Organizations increasingly adopt modular, self-paced platforms that allow employees to acquire targeted skills aligned with emerging technologies. These platforms—such as Coursera, edX, and Udacity—offer stackable microcredentials in areas like machine learning, data ethics, and human–AI interaction (Belwalkar & Maki, 2023). AI itself is often embedded in these systems, personalizing learning paths, recommending content, and assessing progress in real time.

The World Economic Forum (2025) estimates that over 59 % of workers would need training by 2030 due to AI and automation, yet only half currently have access to adequate training. This gap underscores the urgency for organizations to invest in scalable, inclusive learning ecosystems that support career-long development. By embedding lifelong learning into their strategic frameworks, firms not only future-proof their workforce but also foster a culture of adaptability and innovation (Palenski et al. 2024).

These new learning paradigms also promote equity and inclusion. By offering flexible formats and industry-recognized credentials, they empower diverse populations—including women, mid-career professionals, and workers in underserved regions—to participate meaningfully in the digital economy (Varsik &Vosberg, 2024). In this way, continuous training becomes not only a catalyst for performance, but also a lever for social mobility and sustainable organizational growth.

Altogether, continuous training—when intelligently aligned with AI capabilities—enhances workforce readiness, strengthens ethical deployment, and anchors organizational resilience in a rapidly evolving technological landscape .

2. Research Methodology

This study adopts an exploratory qualitative approach, consistent with the work of Bühlmann and Tettamanti (2007) on emerging organizational phenomena, Charrière and Durieux (2003) on organizational dynamics, and Thiétart (1999) on conceptual development in complex environments. This interpretivist orientation is particularly appropriate for exploring how actors perceive and experience technological change, allowing rich, contextualized insights rather than statistical generalization. The choice of this methodological design is driven by three main factors: the emerging nature of Artificial Intelligence (AI) within Tunisian industrial contexts, the absence of established theoretical models to assess its organizational impact, and the need to capture the mechanisms and subjective meanings underlying AI's integration—particularly regarding workforce development and organizational transformation. Given the multidimensional nature of AI adoption, this approach is well suited to examining employees' lived experiences and perceptions of intelligent systems and associated training practices. It allows for a deep contextual understanding of how AI reshapes work structures, learning cultures, and intergenerational dynamics within organizations.

2.1. Case Study Context: SOPAL

The case study focuses on SOPAL (Société de Production d'Articles en Laiton), a leading Tunisian industrial firm founded in 1981. SOPAL was selected as a critical case (Yin, 2018) because it exemplifies early and advanced integration of AI technologies in a developing-country industrial context—making it an ideal setting for analyzing how training mediates AI-driven transformation.

SOPAL has distinguished itself nationally through its advanced use of AI across production and management processes. The company specializes in the manufacturing and distribution of sanitary components, water and gas fittings, and has built its growth strategy around continuous product innovation and customer-centric design.

SOPAL's industrial operations reflect a high degree of vertical integration and technical sophistication. Its in-house engineering department employs advanced design and development technologies supporting precision manufacturing processes such as hot forging, gravity casting, high-pressure injection molding, computer numerical control (CNC) machining, robotic polishing, and automated surface treatment (nickel and chrome plating). These advanced systems not only improve operational efficiency but also demand continuous workforce upskilling to manage complex, technology-intensive production chains. With a workforce of approximately 1,000 employees, SOPAL maintains a dominant position in the Tunisian industrial landscape and demonstrates robust competitive capabilities. Its international expansion strategy—anchored in a strong corporate brand—seeks to reinforce its presence across the Maghreb Union, West Africa, and the Gulf region. This strategic orientation reflects both the opportunities and challenges of integrating AI in emerging markets, providing a fertile ground for understanding how local organizations adapt global technologies through targeted training and organizational learning.

In line with its innovation-driven strategy, SOPAL has progressively adopted AI-enabled systems to optimize operations and enhance performance. These include the integration of SEGE X3—an enterprise resource planning (ERP) platform with AI-supported modules for commercial operations and client data management; robotic process automation in polishing and surface treatment units; and predictive analytics tools used for production planning and quality control.

Additionally, SOPAL has implemented a digital HR portal that leverages intelligent workflows to streamline administrative tasks such as leave requests and payroll scheduling. While these technologies improve operational efficiency, they simultaneously redefine employee roles and skill requirements, underscoring the importance of continuous training to ensure effective human–machine collaboration and sustain organizational learning.

Table 1: Participant Profile in the SOPAL Case Study

Participant ID	Gender	Age	Years of Service	Position	Degree of Exposure to/use of AI
C1	Male	47	7 years	HR Director	Daily use of the digital HR portal; oversees HR analytics.
C2	Male	49	11 years	Commercial Director	Daily use of AI modules in the SEGE X3 ERP system for sales forecasting.
C3	Male	44	18 years	Production Director	Operates polishing robots; uses predictive analytics tools for quality control.
C4	Male	58	16 years	Quality/Metrology Manager	Uses AI-enabled metrology software for quality inspection.
C5	Female	39	8 years	Quality and Production Supervisor	Supervises automated processes; uses production data analytics tools.
E1	Female	36	7 years	Sales Employee	Daily use of SEGE X3 ERP for order and customer management.
E2	Female	34	5 years	Sales Employee	Daily use of SEGE X3 ERP for order and customer management.

Source: SOPAL

2.2. Study Sample and Data Collection

The objective of this research is to analyze employees' perceptions of Artificial Intelligence (AI), explore the conditions for effective human–machine collaboration, and assess the influence of generational diversity on digital transformation processes.

The sampling strategy was guided by the principles of theoretical saturation (Glaser & Strauss, 1967) and logical replication (Yin, 1990), ensuring both depth and heterogeneity in the data collected. This purposive sampling approach was designed to capture a wide spectrum of viewpoints, reflecting variations in role, seniority, and digital familiarity within SOPAL. Saturation was considered reached once no new themes emerged and the main analytical categories became stable across participant profiles (roles, hierarchy, and age). Saturation was further confirmed during the final iteration of coding, when no additional categories appeared across the last two interviews, indicating thematic redundancy and analytical completeness.

Following Eisenhardt's (1989) recommendations for case-based inquiry, seven semi-structured interviews were conducted over two consecutive days at SOPAL's headquarters. Each session lasted approximately two hours, allowing participants to elaborate freely on their experiences, perceptions, and expectations regarding AI integration and training practices.

An interview guide was developed based on the theoretical framework, covering four main themes: (1) perceptions of AI and technological change, (2) experiences with training and skill adaptation, (3) perceived challenges and benefits of human–machine collaboration, and (4) intergenerational differences in digital engagement.

This open-ended approach facilitated rich, context-sensitive insights, enabling participants to articulate both rational and emotional dimensions of their experiences.

Participant selection followed a dual diversification logic, ensuring a representative and balanced understanding of organizational perspectives:

- Functional diversity: Five managers and two employees from distinct departments and hierarchical levels, with balanced gender representation. This ensured the inclusion of both strategic (managerial) and operational (employee) perspectives.
- Generational diversity: Four participants aged 30–45 and three aged 45–60, allowing for comparative analysis across age cohorts and highlighting potential contrasts in digital literacy, adaptability, and training expectations.

All interviews were recorded with prior informed consent, then fully transcribed and anonymized for thematic analysis. The research strictly adhered to ethical standards, ensuring voluntary participation, confidentiality, and data integrity, in line with institutional research ethics protocols.

To reconcile analytical precision with participant confidentiality, a systematic coding scheme was implemented. Each respondent was assigned an alphanumeric identifier (C1–C5 for managers; E1–E2 for employees) along with contextual metadata (tenure, age group, gender, role, interview duration). This approach facilitated cross-case comparison and pattern identification while safeguarding anonymity. It also enhanced the trustworthiness and transparency of the analysis by maintaining clear traceability between raw data and emerging themes.

The data collected through the semi-structured interviews were analyzed using a manual thematic coding approach, following the analytical framework proposed by Braun and Clarke (2006). This method was selected for its flexibility and suitability for exploratory qualitative research, allowing themes to emerge inductively from the data while remaining closely aligned with the study's objectives.

The analysis unfolded through several iterative stages. First, during the familiarization phase, all interview transcripts were read repeatedly to gain a holistic understanding of the content and context. Preliminary ideas and patterns were noted in analytical memos to guide the initial stages of coding.

In the first cycle of coding, descriptive and *in vivo* codes—using participants' own words and expressions—were applied to relevant excerpts. This approach preserved the authenticity of participants' perspectives and captured the nuances of their lived experiences regarding Artificial Intelligence (AI) and training practices.

The second cycle of coding involved refining and grouping these initial codes into broader categories and emerging themes. Through constant comparison across interviews, conceptual similarities and divergences were identified, progressively consolidating these categories into four major analytical themes: (1) perceptions of AI and technological change, (2) experiences with training and skill adaptation, (3) human–machine collaboration and workplace transformation, and (4) intergenerational dynamics in digital engagement.

Throughout the process, analytical memos were maintained to document reflections, interpretive choices, and coding decisions, ensuring transparency, traceability, and methodological rigor. The manual nature of the analysis enabled the researcher to remain deeply engaged with the data and sensitive to contextual meanings, while still applying systematic and replicable procedures of qualitative analysis.

This interpretive and iterative approach ensured that the resulting themes were both empirically grounded in participant narratives and theoretically coherent with the research framework, providing a rich and credible understanding of how AI-related transformations are experienced within SOPAL

2.3. Structure and Objectives of the Interview Guide

The analysis of interviews conducted at SOPAL serves several interrelated objectives. First, it explores how age influences employees' perceptions of Artificial Intelligence technologies and their integration into the workplace. Second, it examines differences between managerial and operational staff, highlighting how hierarchical positions shape attitudes toward digital transformation. Third, it investigates how organizational tenure affects openness to technological innovation and change. Finally, it identifies both shared and divergent expectations and concerns across professional profiles, offering a nuanced understanding of how AI-related developments are experienced within a diverse workforce.

The interview guide was designed around four analytical themes, aligned with the study's objectives and theoretical framework: (1) perceptions of AI and technological change, (2) training and skill adaptation, (3) human–machine collaboration and workplace transformation, and (4) intergenerational dynamics in digital engagement.

It consisted mainly of open-ended questions, allowing participants to express themselves freely and provide detailed narratives that accurately reflect their perceptions, experiences, and interpretations. The main goal was to explore the role of AI in employee training programs and its influence on the evolution of professional methods and practices within the organization. This qualitative design made it possible to capture both factual and emotional dimensions of employee experiences. The complete interview guide is presented in Appendix A.

To facilitate analysis and ensure clarity in presenting findings, results are displayed in tabular format, highlighting recurring themes, points of convergence and divergence, and broader structural patterns emerging from participant narratives.

3. Analysis of Results

This section presents the findings from the semi-structured interviews conducted with SOPAL employees.
The analysis was carried out through a manual thematic coding process following Braun and Clarke's (2006) framework. Four major themes emerged from the data: (1) Perceptions of Artificial Intelligence and technological change, (2) Experiences with training and skill adaptation, (3) Human–machine collaboration and workplace transformation, and (4) Intergenerational dynamics in digital engagement.

The insights reveal a nuanced understanding of how AI integration is experienced across hierarchical levels, generational groups, and functional domains within the organization. They highlight both convergences and divergences in employee perceptions, reflecting the complex interplay between technological innovation, training practices, and evolving organizational structures.

3.1 Perceptions of Artificial Intelligence

The perception of AI at SOPAL is marked by pragmatic optimism. Employees across hierarchical levels recognize its transformative potential while maintaining a human-centered view of work. AI is not seen as a threat but as a tool that must be intelligently integrated to complement—rather than replace—human expertise.

The Quality and Metrology Manager (C4) articulates this balance clearly. His department benefits from AI-driven software updates and data optimization, which reduce routine errors and streamline operations. Yet, he resists the notion of full automation:

"*It's a pleasure to work with technology that evolves with our times and fits SOPAL's constant need for product improvement. But in our function, replacing humans is not feasible. Software updates eliminate routine tasks, but machine operation still requires human presence.*"

This reflects a broader organizational stance: AI is welcomed for its efficiency, but its deployment remains bounded by the irreplaceable value of human judgment and technical intuition.

The HR Director (C1) situates AI within SOPAL's digital transformation strategy, highlighting both efficiency and human connection: "*We've digitized our HR portal and internal communications to improve efficiency. But let's be clear—AI is designed by humans and used by humans. It's a tool, not a substitute for human connection.*"

His emphasis on co-construction and targeted communication suggests that SOPAL's digitalization process is participatory rather than top-down—an important indicator of organizational maturity in managing change.

The Commercial Director (C2) offers a more ambivalent view. While praising AI's operational benefits—particularly in logistics and remote work—he also voices concern about potential redundancy: *"AI is extraordinary—it speeds up tasks and supports remote work. But if it keeps advancing, it could eventually replace me."*

This tension between opportunity and vulnerability is typical of middle-management roles in AI-augmented environments, where strategic oversight is increasingly shared with intelligent systems.

The Sales Employees (E1 and E2) provide a frontline perspective. Their experience with the SEGE X3 software illustrates how AI can enhance reliability and enable remote work: *"Since SEGE X3 moved online, we've had fewer disruptions. During COVID and even now, we can work remotely without interruptions. That's essential for our department."*

However, they emphasize the limits of AI in client-facing contexts: *"AI saves time, but it can't replace the human presence—especially in sales. Clients expect empathy, reassurance, and clear answers. That's something only a person can provide."*

Their reflections highlight that, while AI optimizes back-office functions, it cannot replicate emotional intelligence and relational nuance in customer service.

Finally, the Production Director (C3) synthesizes these perspectives, viewing AI as essential to competitiveness when paired with human ingenuity: *"AI helps us improve product quality and employee performance. Human intelligence and machine capabilities complement each other—it's like a marriage."*

His metaphor of "marriage" captures the ethos of SOPAL's approach—a deliberate, symbiotic integration of technology and talent.

3.2 Training and Skill Adaptation

Training at SOPAL is treated as a proactive, strategic investment rather than a reactive necessity. The interviews reveal a culture of structured learning aligned with both organizational goals and individual development. AI integration has intensified the need for continuous upskilling, but SOPAL appears well-prepared to meet this challenge.

The Quality and Metrology Manager (C4) describes a tiered training system linked to performance metrics and financial incentives: *"Training tools remain theoretical; to be effective, they must be followed up. But at SOPAL, we're certainly not lacking in training."* His emphasis on follow-up suggests an understanding of training as a continuous process requiring reinforcement and contextualization.

The HR Director (C1) connects training directly to SOPAL's international growth strategy:

"There's no shortage of training at SOPAL. It's essential to our goal of becoming a leader in Africa." This reframes training as a strategic lever for competitiveness, beyond its HR function.

The Sales Employees (E1 and E2) illustrate SOPAL's bottom-up learning culture, where employees co-design training plans: *"At the beginning of each year, our department proposes training based on our needs—advanced Excel, time management, communication. If we express a specific need, the company never refuses."*

They also link training to well-being: *"Psychologically, I feel much more comfortable thanks to these opportunities for growth."*

This connection between learning and psychological security underscores the human dimension of digital transformation.

The Production Manager (C5) highlights the inclusivity of training programs, which combine technical and psychosocial dimensions: *"The goal is to improve skills for both qualified and unqualified employees. We use the native language and offer modules on stress, belonging, and the value of work."* His comment demonstrates an awareness that adaptation to AI involves both cognitive and emotional resilience.

Finally, the Production Director (C3) and Commercial Director (C2) reaffirm the institutional commitment to training through annual needs assessments and dedicated budgets. As C2 notes: *"We invest heavily in training—it helps us improve processes, facilitate work, and maintain our competitive edge."*

Across all accounts, training emerges as a central organizational resource, sustaining motivation, productivity, and engagement in the face of technological change.

3.3 Human–Machine Collaboration and Workplace Transformation

SOPAL's experience reflects a deliberate effort to foster collaborative coexistence between human labor and intelligent systems. Managers and employees alike describe AI as an enabler of performance rather than a disruptor of jobs.

The HR Director (C1) underscores that human oversight remains indispensable: *"Even with automation, human supervision and verification are essential. Machines perform, but humans ensure quality and consistency."*

Similarly, the Production Director (C3) views AI as an opportunity to enhance human potential, not diminish it: *"AI doesn't replace workers; it enhances their capabilities. It allows us to focus on innovation instead of repetitive control."*

This orientation toward complementarity rather than substitution aligns with SOPAL's participatory digital strategy. The interviews also suggest that AI deployment has encouraged horizontal collaboration between departments, increasing communication and knowledge exchange.

However, employees acknowledge that adapting to these hybrid systems requires ongoing coordination, feedback loops, and trust-building. This reinforces the view of AI integration as a social as well as technological transformation, demanding sustained attention to leadership, learning, and cultural cohesion.

3.4 Intergenerational Dynamics in Digital Engagement

Generational diversity plays a significant role in shaping how employees experience AI adoption.
The Commercial Director (C2) observed that younger employees adapt more quickly to AI tools, while older colleagues often need more time and reassurance: *"Younger colleagues are more comfortable with digital tools. For others, it takes longer—but with proper guidance, everyone can benefit."* This generational divide underscores the importance of differentiated training approaches that account for varied learning speeds and familiarity with digital systems.

The HR Director (C1) highlights mentoring and peer learning as essential mechanisms for bridging this gap: *"We pair experienced employees with younger ones who are digitally fluent. It's not just about learning the tools; it's about mutual respect and shared progress."*

This demonstrates that AI integration at SOPAL functions as a collective learning process. The Sales Employees (E1 and E2) confirmed that collaboration and mutual support were critical to sustaining engagement: *"We help each other learn. It's not just about technology—it's about how we work together to make it useful."*

Overall, SOPAL's approach fosters inclusive digital transformation, where intergenerational collaboration becomes a source of organizational resilience and shared innovation.

Table 2 : Summary of Findings

Theme	Category	Illustrative Quotations	Interpretation
1. Perceptions of Artificial Intelligence and Technological Change	**Human–Machine Complementarity**	C4: "It's a pleasure to work with technology that evolves with our times... But in our function, replacing humans is not feasible."	AI is perceived as a supportive tool that complements rather than replaces human expertise—reflecting pragmatic optimism.
	Managerial Ambivalence	C2: "AI is extraordinary—it speeds up tasks and supports remote work. But if it keeps advancing, it could eventually replace me."	Middle managers express both admiration and anxiety, revealing tension between opportunity and vulnerability.
2. Training and Skill Adaptation	**Dual Competence Development**	C5: "We use the native language and offer modules on stress, belonging, and the value of work."	Training addresses both technical and psychosocial needs, consistent with the Job Demands–Resources (JD-R) model.
	Structured and Participatory Learning	E1: "If we express a specific need, the company never refuses."	A bottom-up learning culture strengthens organizational absorptive

			capacity (ACAP) and supports continuous skill development.
3. Human–Machine Collaboration and Workplace Transformation	**Leadership Role in Change Facilitation**	C1: "Managers must lead by example… we involve teams in the process to build trust and ensure smooth transitions."	A participatory approach to change management fosters trust and enables successful digital adoption.
	Collaborative Learning Dynamics	E2: "We help each other learn. It's not just about the technology—it's about how we work together to make it useful."	Peer learning and cooperation emerge as critical enablers of effective human–machine collaboration.
4. Intergenerational Dynamics in Digital Engagement	**Digital Fluency Differences**	C2: "Younger colleagues are more comfortable with digital tools. For others, it takes longer—but with proper guidance, everyone can benefit."	Differences in digital literacy across age groups highlight the need for tailored and inclusive training strategies.

Source : SOPAL

4. Discussion of Results

Recent research has emphasized the strategic importance of integrating artificial intelligence (AI) into organizational processes in a deliberate and human-centered manner to fully realize its transformative potential (Dennehy et al., 2023; Loske & Klumpp, 2021). When intelligent systems are deployed to manage repetitive or analytical tasks, employees are afforded greater cognitive bandwidth to engage in activities that require judgment, creativity, and strategic decision-making. This reallocation of effort contributes to enhanced productivity, innovation, and organizational agility.

Building on the manual thematic coding approach applied in this study (Braun & Clarke, 2006), four major themes emerged—(1) perceptions of AI and technological change, (2) experiences with training and skill adaptation, (3) human–machine collaboration and workplace transformation, and (4) intergenerational dynamics in digital engagement. These themes provide the interpretive framework guiding the following discussion.

Our findings indicate that training functions as the key mechanism enabling this reallocation by developing the organization's absorptive capacity (Cohen & Levinthal, 1990). By facilitating the assimilation of AI-related knowledge, training empowers employees to shift toward higher value-added tasks.

Several authors have argued that AI should not be conceptualized as a substitute for human labor, but rather as a complementary resource that augments human capabilities (Wilson & Daugherty, 2018; Caputo et al., 2024; Scuotto et al., 2024). The findings from the SOPAL case study support this view, illustrating how AI integration enables employees to maintain attentional and analytical capacities while benefiting from digital augmentation. Rather than displacing human roles, AI facilitates a redistribution of cognitive effort toward tasks with higher strategic and relational value. This dynamic between automation and human development also reflects the principle of *organizational ambidexterity* (Tushman & O'Reilly, 1996). Through AI, SOPAL simultaneously exploits existing operational capabilities—enhancing process efficiency and accuracy—while exploring new learning and innovation pathways through continuous training. This balance between exploitation and exploration demonstrates how training initiatives sustain the flexibility required to integrate intelligent systems without destabilizing established work structures. It thus confirms that AI adoption, when coupled with adaptive learning, can strengthen both short-term performance and long-term innovation potential.

This process of functional complementarity observed at SOPAL can be conceptualized as a form of human–AI teaming, in which each party focuses on its comparative advantages. This perspective challenges common fears of automation-induced job displacement. As highlighted by the European Centre for the Development of Vocational Training (CEDEFOP, 2019), the notion of complete human replacement remains largely speculative and overstated. The SOPAL case instead reveals a dynamic of functional complementarity, wherein AI and human expertise coexist and reinforce one another. The success of AI deployment appears to depend on a constellation of organizational conditions, including the autonomy granted to employees, sustained investment in training, and adaptive communication practices that support the integration of digital tools across functional domains. These findings align with the work of Rai, Constantinides, and Sarker (2019), who advocate for a balanced approach in which AI strengthens rather than replaces human potential.

The integration of AI into organizational workflows also necessitates a robust and sustained commitment to employee training. The SOPAL case provides empirical support for the argument that continuous learning is essential for workforce adaptation to digital transformation, as emphasized by Parween (2024) and Keding (2021). SOPAL's training strategy is characterized by structure, responsiveness, and contextual relevance. The organization has institutionalized a proactive learning culture that reflects Berton's (1990) early insights into training as a strategic response to technological change. Regularly scheduled technical and behavioral training modules—ranging from software proficiency to time management and communication—correspond with OECD (2019) recommendations on lifelong learning as a cornerstone of workforce resilience. Within the Job Demands–Resources (JD-R) framework, the training system identified through thematic coding operates as a crucial "resource." By equipping employees to meet the new demands created by AI, it alleviates perceived stress (E1: "*Psychologically, I feel much more at ease*") and enhances motivation and engagement. The prominence of such in vivo statements in the data supports the view that structured learning directly contributes to psychological well-being and performance.

Moreover, SOPAL's training programs are differentiated by occupational role and tailored to local contexts, including the use of native language and context-specific modules. This approach exemplifies the concept of "situated learning" advocated by Dragomir (2010), which enhances relevance, accessibility, and cultural alignment in skill development. The dual imperative of technical and human competencies is clearly reflected in SOPAL's training strategy. While technical proficiency is essential for operating AI-enabled systems, equal emphasis is placed on soft skills such as collaboration, stress management, and interpersonal communication. This dual focus aligns with the conclusions of Makings et al. (2021), who argue for the simultaneous development of technical and relational competencies in digitally augmented work environments.

In addition to its operational benefits, training at SOPAL functions as a driver of talent attraction and retention. The organization's substantial investment in training contributes not only to skill development but also to employee well-being and organizational commitment. This finding supports the work of Kiruthika and Khaddaj (2017), who identify training as a competitive advantage in attracting and retaining talent. The responsiveness to individual learning needs and the flexibility of training pathways reinforce employee engagement and strengthen the psychological contract between employer and employee.

A third thematic dimension, human–machine collaboration, emerged as a defining feature of SOPAL's digital transformation. Leadership and participatory management practices were repeatedly cited as essential in facilitating technological adoption. Managers promote trust through transparent communication and by modeling new behaviors—an approach consistent with co-constructive change management theories. In parallel, peer learning among employees reinforces collective adaptation, illustrating that successful AI integration is as much a social process as a technical one.

The final theme, intergenerational dynamics in digital engagement, adds further depth to the discussion. Younger employees demonstrated greater digital fluency and faster adaptation to

AI tools, while senior staff contributed contextual understanding and process rigor. SOPAL's differentiated training model accommodates these diverse learning rhythms, transforming generational diversity into a source of organizational learning rather than a constraint. This aligns with Cortellazzo et al. (2020), who emphasize that inclusive and flexible training strategies mitigate digital divides and strengthen collaborative learning cultures.

Taken together, the SOPAL case demonstrates that continuous training is no longer a discretionary activity—it is a strategic necessity for successful AI integration. To be effective, training must be embedded in organizational routines, tailored to occupational roles and levels of expertise, balanced between technical and behavioral dimensions, and regularly evaluated to remain responsive to emerging needs. This holistic approach transforms the challenge of technological disruption into an opportunity for organizational development. It confirms that AI, far from diminishing the value of human labor, can amplify it—provided it is accompanied by structured, inclusive, and forward-looking investment in workforce capabilities.

From a managerial standpoint, the SOPAL case suggests a transferable framework for responsible AI adoption. Effective integration requires (1) mapping actual AI use cases—distinguishing predictive or learning modules from simple automation; (2) designing dual-component training that combines technical upskilling with soft-skill development (communication, stress management, collaboration); (3) establishing bottom-up mechanisms for identifying training needs and allocating dedicated budgets; (4) appointing "digital peer tutors" or champions to accompany learning in the workplace; and (5) monitoring 3–4 impact indicators such as product-quality scores, turnaround times, perceived autonomy, and employee satisfaction. These practices translate the human–AI complementarity observed at SOPAL into actionable managerial guidelines. Ultimately, these results illustrate how the four interrelated themes identified through manual thematic coding converge to form an integrated model of digital transformation—linking perception, learning, collaboration, and generational inclusion within a unified human-centered framework.

Beyond its empirical insights, this study also invites a broader theoretical interpretation of how training mediates the relationship between artificial intelligence and organizational transformation.

From a theoretical standpoint, these findings can be interpreted through the complementary lenses of absorptive capacity (Cohen & Levinthal, 1990), the Job Demands–Resources (JD-R) model (Bakker & Demerouti, 2007), and human–AI teaming (Wilson & Daugherty, 2018). Continuous training at SOPAL enhances the firm's *absorptive capacity* by facilitating the acquisition, assimilation, and application of AI-related knowledge, transforming technological change into organizational learning (Parween, 2024; Keding, 2021). Within the JD-R framework, training acts as a key "resource" that offsets the new cognitive and technical demands imposed by AI, thereby reducing stress and sustaining motivation and engagement (Makings et al., 2021). At the same time, the cooperative interaction between humans and AI systems reflects the principle of human–AI complementarity, in which each agent leverages its comparative advantage—human judgment and creativity on one hand, and machine precision and speed on the other (Caputo et al., 2024; Shahzad & Dong, 2024). Viewed through a sociotechnical perspective (Dragomir, 2010), SOPAL's approach demonstrates how technological, organizational, and human subsystems can be aligned to create a resilient and adaptive digital ecosystem. Collectively, these frameworks provide an integrated understanding of how training transforms AI adoption from a technological challenge into a dynamic capability that strengthens organizational performance and employee well-being.

Conclusion

This study has demonstrated that the integration of artificial intelligence (AI) within organizational contexts—when approached strategically and supported by continuous training—can significantly enhance both individual and collective performance. The findings confirm that AI contributes to improved data literacy, more informed decision-making, and a reduction in cognitive biases, thereby enabling employees to better understand performance drivers and engage in higher-value tasks (Soulami et al., 2024; Duan et al., 2019). In commercial functions, AI facilitates more precise customer targeting, deeper analysis of client needs, and more personalized communication strategies, reinforcing its role as a catalyst for responsiveness and customer engagement (Kumar et al., 2019; Ledro, 2022).

However, the benefits of AI do not arise automatically. As illustrated by the SOPAL case, they depend on a deliberate and structured investment in both technical and human competencies. The organization's commitment to differentiated training, contextualized learning, and a culture of collaborative innovation has enabled employees to appropriate AI tools meaningfully and integrate them into their daily practices. This process not only enhances operational efficiency but also contributes to improved job satisfaction and quality of work life, reinforcing the human dimension of digital transformation.

From a theoretical standpoint, the results highlight three interrelated mechanisms that underpin successful AI adoption. First, continuous training acts as a lever of absorptive capacity (Cohen & Levinthal, 1990), allowing employees to assimilate new digital knowledge and apply it effectively. Second, the coexistence of process efficiency and exploration of innovative practices illustrates organizational ambidexterity (Tushman & O'Reilly, 1996), positioning AI as both an exploitative and exploratory tool. Third, through the Job Demands–Resources (JD-R) framework, training emerges as a critical resource that buffers technological stress while enhancing motivation and engagement.

Beyond the immediate organizational context, the study underscores the broader strategic relevance of AI across multiple domains. In industrial operations, AI supports advanced robotics, precision engineering, and expert systems, offering high-performance automated solutions. In customer experience management, predictive algorithms and intelligent virtual assistants enable personalized interactions and foster long-term client loyalty. In human resource management, AI enhances trend analysis, media monitoring, and decision support through machine learning, contributing to more agile and evidence-based workforce strategies.

The complementarity between AI and human expertise thus emerges as a decisive lever for adaptability and innovation. While the concept of human–machine collaboration is well established in the literature, this study emphasizes the importance of employee agency in shaping the outcomes of AI integration. The ability of individuals to master and contextualize intelligent systems ultimately determines their impact on professional practices and organizational value creation.

Nevertheless, the study's scope—limited to a single case and a small number of interviews—calls for replication across diverse contexts to strengthen empirical generalization. Future research could integrate mixed methods, examine sector-specific applications, and investigate how leadership practices, organizational culture, and intergenerational collaboration influence AI adoption trajectories.

In conclusion, this research confirms that AI, when deployed in synergy with human expertise, serves as a powerful accelerator of performance and innovation. It reinforces the strategic importance of investing in workforce development and cultivating organizational cultures that embrace technological change without compromising human value. The SOPAL case exemplifies a virtuous model in which technology and training converge to produce sustainable, high-impact outcomes—affirming that the future of work lies not in substitution, but in intelligent collaboration.

APPENDICES

Appendix A

Interview Guide

Theme 1: Perceptions of Artificial Intelligence
How do you perceive the role of AI in your company today and how do you envision its future development?
In your view, what motivated your organization to adopt AI technologies?
Can you give me a concrete example of how an AI tool changes your daily work?
In your experience, how does AI complement or challenge human skills in your daily work?
Theme 2: Training and Adaptation
How would you evaluate the training you received in relation to AI integration?
Has AI affected your professional competencies or increased the need for continuous learning?
How have the training sessions you attended helped you use these new tools?
Theme 3: Organizational Experience and Expectations
Do you think age or job position affects how employees respond to AI and training?
What support do you expect from your organization to help you adapt to AI-related changes?
Theme 4: intergenerational dynamics in digital engagement
How do you perceive the differences between younger and older employees in adapting to AI tools and digital systems?
In what ways do collaboration and mutual support between generations help employees adapt to technological change?

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