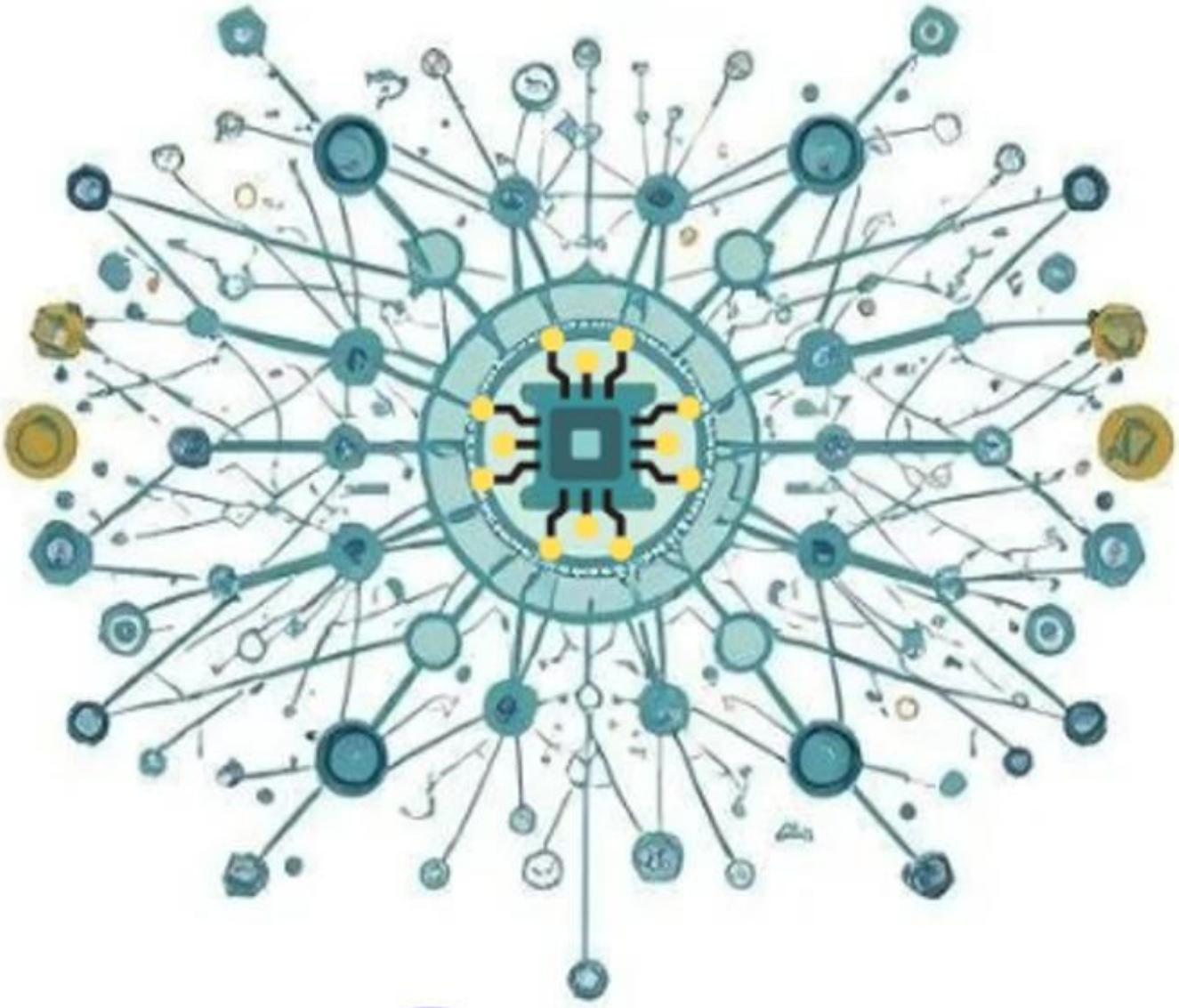
Interdisciplinary Applications of Artificial Intelligence - 2

Editors: Dr. Hasan Küçükoğlu - Dr. Önder Yıldırım



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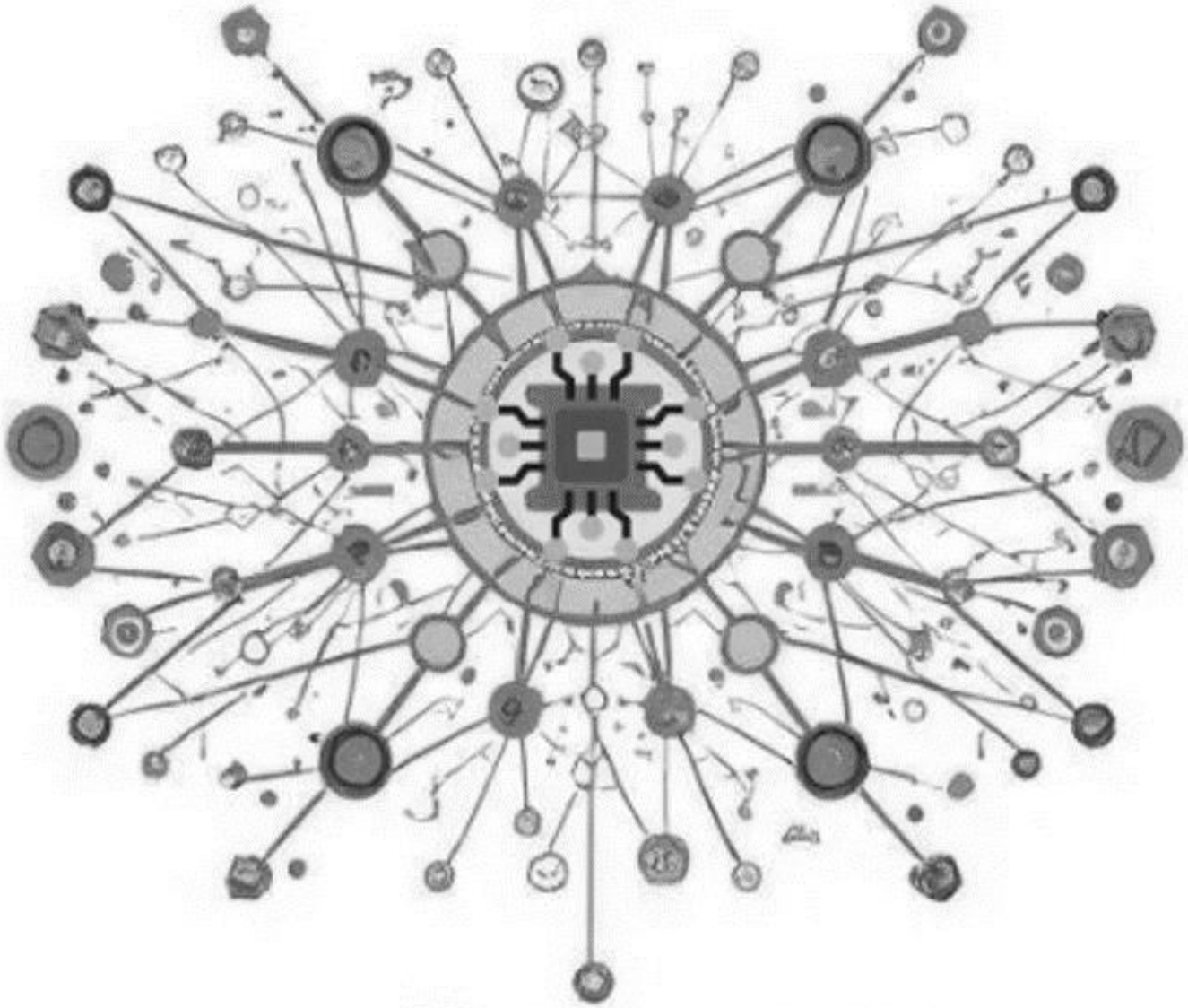

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CHAPTERS

PREFACE..... vii

Chapter 1- Artificial Intelligence-Based Robotic Systems and Applications 1

Chapter 2- Artificial Intelligence Applications in Healthcare..... 24

Chapter 3- Generative Artificial Intelligence, Gamification, and Interactive Learning..... 42

Chapter 4- Artificial Intelligence Applications in Cyber Security..... 65

Chapter 5- Artificial Intelligence in Visual Design..... 90

Chapter 6- The Utilization of Artificial Intelligence in the Domain of Content Creation within Digital Media..... 100

Chapter 7- Artificial Intelligence Applications in Businesses 111

Chapter 8- Artificial Intelligence Applications in Human Resource Management 130

Chapter 9- Artificial Intelligence Applications in Marketing and Sustainability..... 142

Chapter 10- Artificial Intelligence in Financial Sytems..... 162

PREFACE

Education, science, technology, and society are being reshaped by the rapid evolution of artificial intelligence. As AI systems become more capable, their effects extend far beyond technical domains, influencing how we work, learn, communicate, govern, and create value. The true benefit of artificial intelligence, however, emerges only when it is guided by responsible, interdisciplinary, and human-centered approaches.

Interdisciplinary Applications of Artificial Intelligence – 2 has been prepared with this vision in mind. Building on the foundations established in the first volume, this book explores how AI is transforming diverse fields—from robotics and healthcare to business, digital media, cybersecurity, and education-related practices. Our aim is not simply to present technological advancements but to examine how AI can meaningfully integrate with human expertise, ethics, creativity, and social responsibility.

This volume brings together contributions from scholars and practitioners who approach AI from different perspectives. Each chapter offers conceptual insights, real-world examples, and reflections on opportunities and risks. Readers will encounter discussions that span intelligent systems, organizational decision-making, creativity, innovation, and sustainability—all connected by the unifying theme of artificial intelligence.

The book opens with an exploration of AI-based robotic systems, examining architectures, learning methods, applications, and ethical considerations. Subsequent chapters delve into AI in healthcare, presenting diagnostic support, clinical decision systems, and patient-centered innovations; generative AI, gamification, and interactive learning, highlighting how intelligent tools reshape educational engagement; and AI-driven cybersecurity, addressing advanced threats, defense strategies, and resilience.

Further sections investigate AI in visual design, digital media content creation, and enterprise applications, revealing how creativity, communication, and business processes are being reimagined. The volume continues with chapters on human resources management, marketing and sustainability, and AI in finance and banking, offering perspectives on workforce transformation, strategic decision-making, risk management, and ethical responsibility in data-driven environments.

Across all chapters, recurring themes emerge: the need for transparency, accountability, sustainable development, data security, and respect for human dignity. Rather than viewing artificial intelligence as a replacement for human capability, this book treats it as a partner—a powerful instrument that can enhance human judgment, expand opportunities, and support more equitable and informed societies when thoughtfully designed.

This work is the result of dedicated collaboration among experts from multiple disciplines. We are grateful to all authors whose insights, research, and experiences shaped this volume. We also hope that this book will serve not only as a reference but also as an invitation—encouraging new research, responsible innovation, and critical dialogue about the future roles of artificial intelligence.

We believe that Interdisciplinary Applications of Artificial Intelligence – 2 will guide researchers, educators, professionals, and policymakers who seek to understand and apply AI thoughtfully. We wish you an inspiring and reflective reading journey as you explore the many ways artificial intelligence intersects with human life and societal progress.

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Chapter 1- Artificial Intelligence-Based Robotic Systems and Applications

Önder Yıldırım

Chapter Highlights

- Robotic systems have evolved from rule-based automation to embodied agents that perceive, learn, and decide.
- Modern robotics has become scalable and modular through layered/hybrid/distributed architectures and the ROS/ROS2 ecosystem.
- The algorithmic core is shaped by the combination of deep-learning-based perception, reinforcement learning, and planning under uncertainty.
- Industry, healthcare/surgery, agriculture/greenhouses, service, and social robotics represent the most visible interdisciplinary application domains of AI–robotics integration.
- Digital twins, embodied AI, and generative/LLM-based approaches strengthen sim-to-real transfer, natural-language task specification, and closed-loop learning.
- The net climate impact of robotic transformation depends on factors such as energy mix, rebound effects, and governance capacity; efficiency gains alone are not sufficient.
- In ethics and safety, the key challenge is embedding accountability, human oversight, and safe/cyber-secure design principles into systems engineering.
- Future directions are likely to focus less on full autonomy and more on human–robot collaboration and "human-compatible" objective setting.

Introduction

Robotic systems had begun as automation tools used in routine tasks based on the rule stored and lacked context-awareness at an initial stage. This methodology, however, was limited by preventing robots to operate effectively in complex and unpredictable human-shared environments (Brady, 1985; Nilsson, 1997; Siciliano & Khatib, 2016; Vanderborght, 2020).

Breakthroughs in AI Madhavan has helped basically solve these challenges. With advances in machine learning, deep learning, and computer vision, robots transformed from machines that followed predefined commands to intelligent systems with capabilities of sensing their environment, learning from interactions with the environment, and responding to changes (Neapolitan & Jiang, 2018; Lu, 2021).

As a result, the definition of autonomy in robotics has evolved. The classical, rule-based approaches of robotic systems had limited decision trees and deterministic control designs, while AI robotics platforms develop autonomy based on learning through probabilistic inference, learned-based control strategies, as well as feedback loops (Collendanchise & Ögren, 2018). For this reason modern robots are not only considered as algorithmic systems, but also embodied intelligent entities whose behaviour is secondary to the interaction between body, environment and action (Duan et al., 2022).

And the evolution of robotics has been further accelerated by the inclusion of large language models and generative AI. Robots are getting more and more capable of interpreting c ommands expressed using natural languag e, planning taking into account the world state ora range of plan is considered to be w orld state changes, an d doing quite evolved pretty long actions (Wang et al., 2025). Such developments call for robots to be considered not only as purely technical objects but also as socio-technical agents (Russell, 2019).

Nowadays, AI-based robot systems are fully exploited in numerous application fields including industrial production, healthcare and surgery, agriculture and environmental monitoring, service sectors, social robotics and critical-infrastructure systems (Lu 2021; Vanderborght 2020). This wide spectrum of applications situates robotics as an interdisciplinary area and there are economic, environmental, ethical and social aspects.

This is discussed from the basis of the concept and architecture design, algorithmic solution strategies and interdisciplinary application areas, with an integrated assessment framework considering results for sustainability, safety and ethical aspects.

Artificial Intelligence and Robotic Systems: Studies in Organic Morphology

Hitherto, the interaction between AI and robotics has evolved reciprocally. While AI improve in robots perception and decision-making, robotic systems create an opportunity to evaluate AI algorithms and allow them to learn

through their interaction in the environment. This interdependency hasbeen a main facilitator of the successful development of robots with cognitive capabilities (Nilsson, 1997; Brady, 1985; Siciliano & Khatib,2016).
AI-driven robotic system conceptually comprises of three main units:

- Perception,
- Cognition and decision-making, and
- Actuation.

Through sensors, the robot makes observations of its environment in the perception layer. These data, coming from different multimodal sensors (cams, lidar, radar, tactile sensor and biometric detector) may be noisy, incomplete and uncertain (Franceschetti, 2018).

At the cognitive level, sensor data are interpreted into meaningful descriptions and decision is made. At this stage artificial intelligence techniques such as machine learning, deep neural networks, probabilistic models and behavior trees are regularly used. In particular, behavior trees are favored as they enable modular and explainable representation of more complex robotic behaviors (Collendanchise & Ögren, 2018).

Execution in the physical world is subsumed by the actuation layer. The control of movement, including motor control, motion planning and force-feedback processes are among the primary components of this stage. Adaptive control and reinforcement learning based on AI techniques let robots adapt to dynamic environments (Neapolitan & Jiang, 2018).

The hierarchical cooperation of these three layers, not only locates robotic systems as perceiving entities but also incorporates them as innate cognitive agents in the environment which interact continuously and learn and refine behavior. The embodied AI viewpoint not only deepens the theoretical roots of modern robotics, but also opposes the thinking that intelligence solely comes from mind or algorithm, and highlights intelligence as a manifestation of dynamic coupling between body and environment, interaction (Duan et al., 2022; Lu, 2021).

Architectures of AI-Driven Robotic Systems

The performance of AI-based robot systems hinges not only on the quality and capabilities of algorithms involved but also crucially in how these algorithms are combined with perception, control and actuation. It is for this reason that robotic architectures are considered as the basi c structural frame works 10 upon which AI techniques can be moved into live property based systems. Classical monolithic structures have evolved toward modular, distributed and reconfigurable ones that allow for the establishment of scalable, flexible and highly autonomous robotic systems (Franceschetti, 2018; Lu, 2021; Siciliano & Khatib, 2016). Modern robotic topologies put learning, human–robot interaction, and safety at the center of design on par with perception and control. In this sense, they are regarded as a practical model of Embodied Intelligence (Duan et al., 2022).

Layered Robotic Architecture

One of the most common architectural methods in AI-based robots is a layered architecture. In this architecture, the whole system is decomposed into perception, decision-making, and controller components. The layered architecture facilitates the development and update of individual modules, contributing to ease the overall system complexity (Nilsson, 1997; Siciliano & Khatib, 2016).

The sensing layer processes measurements collected by sensors and uses approaches like computer vision, sensor fusion, and state estimation. Deep learning-based sensing provides promising benefits in environmental perception, especially in dynamic and uncertain scenarios (Neapolitan & Jiang, 2018).

The layer of decision-making includes scheduling, learning, and reasoning operations on which reinforcement learning, probabilistic reasoning, hierarchical planning are focused (Lu, 2021). Control layer the control layer translates high-level decisions into physical actions and is responsible for the safe interaction with the environment by implementing adaptive controlled policies. Advantages in reliability and reusability are some of the most apparent advantages that one is guaranteed when utilising layered architectures, yet they might have their limitations for high autonomy dependent and real-time responsive systems (Franceschetti, 2018).

Behavior-Based and Hybrid Architectures

Behaviour-based architectures were created to address these deficiencies. They only react to stimuli from the environment and are based on parallel execution of simple behavior modules, not intensive planning. These architectures are well suited for challenges that require quick real-time responses (Brooks, 1991; Collendanchise & Ögren, 2018).

Hybrid architectures are quite common in modern robotics. These balance the reactive nature of behavior-based systems with planning and learning in layered architectures, allowing the robot to react to changes in the immediate environment while also accomplishing long-term strategic objectives. Within this scenario, behavior trees have emerged as a widely used tool for modeling the robotic behavior and affording hierarchical and modular representations of robot behavior that further explainable system (Collendanchise & Ögren, 2018).

Distributed Systems and ROS-Based Architectures

Middleware and distributed architectures are playing an increasing strategic role in more complex robotic systems. ROS and ROS2 are indeed more or less standards for robotic software development. In the context of ROS-based architectures, sensor data, control commands and AI modules can be connected through nodes (Siciliano & Khatib, 2016; Quigley et al., 2009).

ROS2 adds support for real-time communication, improved secure messaging, deterministic timing and multi-robot capabilities to allow AI-based autonomous systems deployments in industrial and safety-critical applications. These features are vital for deploying perception deep-learning modules, large language models and decision-making components (Lu, 2021; Wang et al., 2025).

Digital Twins and AI-Driven Architectural Extensions

In recent years, robotic architectures have been extended with digital twins. A digital twin is a high-fidelity virtual representation of a physical robot, enabling simulation, optimization, and predictive maintenance. Digital twin environments are frequently used to train AI algorithms before deploying them into real systems, cost effectively and safely (Pastor-Escuredo et al., 2024).

This concept is gaining prevalence in industrial manufacturing and surgical robotics, which permits the testing and enhancement of systems in virtual worlds before they have to be used. Digital Twins additionally contribute to the architectural realization of Embodied AI (Duan et al., 2022).

Security and Ethical Issues in Architectural Design

In AI-oriented robotic architectures security and ethics are not second-thoughts, but rather considered early in the design process. Since autonomous decision-making systems could generate unintended consequences, it is necessary to add explainability, human-in-the-loop control, and safe-learning into AI (Yampolskiy, 2019).

In fields such as health care, defense, and critical infrastructure, responsibility, controllability and shared responsibility between humans and machines are now treated as central architectural principles. In this sense, the human-compatible AI perspective provides a fundamental paradigm for promoting future robotic architectures (Abassi, 2019; Russell, 2019).

Algorithms: Learning, Perception, and Robotics

The salient characteristic of these AI-based robotic systems, is their capability to sense inputs from the environment, have those inputs act on a cognitive framework which makes decisions based upon uncertainty. These functions change the robots from simple mechanical to cognitive executants. At the heart of this transformation lies a set of algorithms that directly control actions robotic systems take as they interact with their environments (Lu, 2021; Neapolitan & Jiang, 2018; Siciliano & Khatib, 2016). A more recent "embodied AI" view has expanded the evaluation of robotic algorithms to include more than just the perception–action loop as a data-processing pipeline, but also as an alternative method for learning and generalization from that interaction with the environment itself (Duan et al., 2022).

Vision: From Sensory Data to Semantic Representation

The perception is the crucial task for a robot to perceive its environment with sensory data. Data from cameras, lidar, radar, accelerometers and biosensors collected over multiple sources is often high-dimensional, noisy and incomplete. Therefore, perception problems have now become so involved that traditional rule-based techniques are no longer able to solve them (Franceschetti, 2018; Siciliano & Khatib, 2016).
Recent developments in deep learning have led to remarkable progress of robotic perception, especially in computer vision. The wide application of CNN in object recognition, scene understanding and visual tracking could improve the reliability of robots working environment as well (Neapolitan & Jiang, 2018). In surgical and healthcare robotics, perception systems based on deep learning have also been able to obtain high scores in tasks of interest, including tissue recognition and instruments detection (Tasdemirci et al., 2026).

Perception is also an integral part of sensor fusion. Exploring combined information from multimodal sensors overcomes the drawbacks of a single modality, and thereby improves environment perception. This strategy has been widely used in AMR and US systems for localization, mapping and obstacle detection (Lu, 2021; Siciliano & Khatib, 2016). In addition, the embodied AI literature focuses on evaluation protocols that do not treat perception as addressing "accuracy," but rather as engendering performance overall in task-oriented interaction such things as navigation, exploration, and embodied question answering (embodied QA) (Duan et al., 2022).

Learning Strategies: Experience to Knowledge

In an AI-based robot system, learning is the robot's ability to take knowledge from experience and to improve its performance over time. In this context, machine learning is the principle tool which empowers robots to perform tasks that have not been pre-specified. Supervised and unsupervised learning algorithms are typically used for the perception, classification, and clustering tasks (Neapolitan & Jiang, 2018).

Robotics has a strong presence in reinforcement learning. In reinforcement learning, a robot learns policies from its own experiences with the environment under reward–penalty signals. This method provides a viable solution to intractable problems of control and large state space (Lu, 2021). Deep learning-based techniques have shown that robots can learn human-like behaviors in playing games of grasping, locomotion, manipulation and other tasks with fine express control (Lu, 2021).

Recently, learning has gone beyond traditional methodologies by leveraging large language model (LLM)-based methods. LLMs can act as high-level policies or planners in the problems of goal specification, plan generation, symbolic sub symbolic interfacing and multi-step referencing (Kim et al., 2024; Zeng et al., 2023). The vision-language-action (VLA) program, for instance, introduces novel architectures that connect knowledge at web scale with robotic control and project actions onto a joint representation space (Brohan et al., 2023).

Nevertheless, the deployment of learning-based algorithms with physical robots introduces important issues in terms of safety and generalization. Mistakes during learning in the real world may lead to physical damages, therefore making virtual enparation and digital twins important for mitigating risk (Pastor-Escuredo et al., 2024). The AI safety literature also emphasizes the importance of systematically dealing with risks like "unintended behavior", "reward misspecification" or "out-of-distribution (OOD) states" in learning setting(Amodei et al., 2016).

Interaction and Reasoning: Autonomy in Uncertain and Devided World

Attention to decision making, where the information produced by perception and learning processes is translated into action. Robotic system often requires solutions to decision problems when facing uncertainty, partial observability and dynamical changes in environment. As a result, probabilistic models and planning algorithms serve as critical building blocks for AI-based robotic systems (Nilsson, 1997; Siciliano & Khatib, 2016).

Markov Decision Processes (MDPs) and Partially Observable Markov Decision Processes (POMDPs) are the prevalent mathematical models used in robotics to deal with strategic, long-term decision-making. They are especially good at auto navigation, task planning and multi-agent coordination (Neapolitan & Jiang, 2018). Behaviour trees and hierarchical planning methodologies nevertheless enable to shape the decision-making process in a modular, scalable and comprehensible way (Collendanchise & Ögren, 2018).

In the LLM-based work in the robotics literature, there are two main lines of progress on decision-making and planning: task-specification and plan generation through natural language (Kim et al., 2024; Zeng et al., 2023), and online adaptation of plans based on perceptual feedback (Zeng et al., 2023). Embodied multimodal models as PaLM-E incorporate visual and linguistic context to generate more context-aligned commands and plans (Driess et al., 2023). The RT-2 line of work tries to connect more end-to-end planning and control via action tokenization (Brohan et al., 2023).

In healthcare/surgical robotics, decision-making systems are often configured to work in a human-in-the-loop manner. In these systems, AI serves as an instrument for the surgeon and not a decision-making tool; the ultimate decision authority still lies with the human operator. This is a trade off that tries to harmonize autonomy and security (Tasdemirci et al., 2026).

Bounds and Prospects for Algorithmic Methods

Although AI-driven algorithms has resulted in major progress to the robotic intelligence, existing methods have some drawbacks. Data dependencies, interpretability, out-of-distribution behavior and surprises by autonomous systems are some of the challenges we have come to associate with cutting-edge robotic algorithms today (Amodei et al., 2016; Yampolskiy, 2019).

Modern research is therefore more and more concerned with explainable AI, safe learning, and human-centered robotics. In particular, the "human-compatible" AI agenda is shaping algorithmic design considerably through its

focus on ensuring that robotic decision making techniques stays in line with human values and respects controllability (Russell, 2019). In the field of LLM–robot integration, issues such as prompt development, plan validation, safe tool use, and alignment between task specification and execution have been identified as a key research challenge at the interface of technical and ethical concerns (Kim et al., 2024).

Domain Applications: Industry, Health Care, Agriculture, Service and Social Robotics

The effects of AI-based mechatronic systems can be clearly understood in various areas of applications. Robots endowed with perception, learning and decision making not only perform physical tasks but also serve multidimensional purposes such as process optimization, human– machine cooperation or sustainability. The finalized section discusses the principal fields of applications for AI-based robotic systems focusing on cross-disciplinary aspects (Lu, 2021; Siciliano & Khatib, 2016; Vanderborght, 2020). Over the last years, the embodied AI and large scale foundation model paradigms have specifically reframed how robots in different domains are to be understood: no longer mere "task executors" but as agents that learn and generalize through their interactions with the world (Duan et al., 2022).

Industrial and Manufacturing Robotics

One of the oldest and most widely used application fields for AI-based robotic systems is industrial robotics. As opposed to their predecessors, the classical industrial robots, which have highly accurate executing of preprogrammed tasks, now, AI has provided them with potentialities like flexible manufacturing, fault diagnosis and detection ability, adaptive control and human 18 robot collaboration (cobots) (Franceschetti, 2018; Siciliano & Khatib, 2016).

Machine learning and computer vision methodologies are widespread in quality assurance, visual examination a nd predictive maintenance. Deep learning based visual inspection systems, in particular, can achieve better defect detecting performance on production lines (Lu, 2021). Methods relying on large language models (LLMs) can further elevate these systems beyond mere "detection" by providing explanations and justifications of the detected anomalies as well as suggesting actions to human operators, thereby empowering human–robot collaboration (Tasneem & Pieters, 2026; Kim et al., 2024).

The environmental consequences of industrial robots has also emerged as a critical area for research. AI-driven intelligentize and automation of robot can improve energy efficiency and lower carbon emissions, but with spatial overflow effects on regional disparity (Luo et al., 2026). These results suggest that industrial robotics is an issue not only of economic performance but also of environmental sustainability. At the landscape level, as a climate mitigation tool, AI could enable automated processes to be optimized for energy intensity and contribute to reduced emissions—but the extent of impact depends greatly on governance and scope (Kaack et al., 2022).

Chapter 1: Artificial Intelligence-Based Robotic Systems and Applications

Healthcare and Surgical Robotic Systems

In the healthcare sector AI-based robotic systems have managed to rapidly penetrate and create significant value. Surgical robots increase patient safety and the rate of success in minimally invasive procedures, as they provide a higher precision and better control (Tasdemirci et al., 2025). The development of AI enhanced surgical robotic systems is detailed using concepts like image-based sensing, decision-support, intelligent workflow management and training/feedback (Liu et al., 2024).

AI models are key players in surgical planning, image interpretation and intraoperative decisions. Image processing based on deep learning, allows for real-time detection of surgical instruments and anatomical structures, decreasing the surgeon's cognitive workload (Tasdemirci et al., 2026). AI-aided feedback systems are also very helpful for surgical education to aide in performance assessment and skill building (Ma et al., 2024).

In medical robotics, autonomy is generally limited because of ethical and legal issues. As a result, AI components are typically developed as decision aides, with ultimate responsibility and authority retained by human experts. This design principle is considered as fundamental for both safety and accountability (Russell, 2019; Yampolskiy, 2019).

Agricultural, Greenhouse, and Environmental Robotics

Agriculture and environmental applications are domains in which AI-based robotic systems are closely aligned with sustainability objectives. Smart agricultural robots perform tasks such as crop monitoring, disease detection, precision spraying, and automated harvesting, thereby increasing productivity while optimizing the use of resources such as water, fertilizers, and pesticides (Al-Najadi et al., 2025; Lu, 2021). In greenhouses and controlled-environment agriculture, autonomous systems are increasingly used for climate control, irrigation optimization, and energy management (Al-Najadi et al., 2025).

Computer vision and machine learning methods are successfully utilized in problems such as plant health monitoring, early disease diagnosis, input reduction and environmental friendly operations (Lu, 2021). The digital-twin and simulation-based methodologies allow agricultural robots to be tested in different climate and terrain conditions before being deployed, increasing safety and robustness on the field (Pastor-Escuredo et al., 2024). This view aligns with the "application context" emphasis in the AI–climate alignment literature (Kaack et al., 2022).

Service Robots and Human–Robot Interaction

In the service industry, AI powered robotic systems directly and constantly collaborating with human beings are widespread. General-purpose service robots used in hotels, shopping centers, hospitals and public buildings to aid navigation, provide information, or assist with physical transport and logistics (Vanderborght, 2020; Siciliano & Khatib, 2016).

In this context, AI methods like natural language processing (NLP), emotion recognition and social behavior modeling play a leading role. Studies in human–robot interaction emphasize that making robot behaviors explainable, consistent and predictable is crucial to improve social acceptance (Lu, 2021). The applications of large language models in robotic systems offer new prospects for building natural and context-aware interactions (Kim et al., 2024).

Yet, because LLM-based systems could go beyond the conversational functions including e.g. task planning, tool use or environment interaction--, concerns like task- execution alignment, safety monitoring and fault-tolerance need to be tackled both at architectural and operational levels in service robotics (Kim et al., 2024; Russell 2019).

Social Robotics and Societal Impacts

Social robotics' is not just about the functional utility of robots, but also their capability for emotional and social interaction. Education and elderly-care robots have been developed that are intended to respond to the cognitive and emotional needs of the user in these activities (Papadopoulos et al., 2022).

In this area cultural context is especially important! Adoption and influence of social robots: these are significantly influenced by cultural norms, perceptions about privacy, the tendency to trust, ways of communicating (Papadopoulos et al., 2022). The embodied AI view also extends the objectives of comparison for social robot design by stressing that social cues are not only linguistic, they are multimodal (e.g., body orientations and postures, spatial distances between interactants, gaze directionality, temporal synchrony) (Duan et al., 2022).

Social robots' social acceptance determines not only by the technical performance, but also trust, privacy protection, transparency, and ethical alignment. Accordingly, social robotics is a field where one needs to pay closer attention to the impact on society and reflect critically on norms and values toward AI-based robotic systems than its technical side (Russell, 2019; Yampolskiy, 2019).

Digital Twins and Embodied AI and Generative Robotics

Recent advances in AI-based robotics technologies have not been restricted to incremental algorithmic improvements; they have also resulted in deep changes in the ways we design, simulate and teach these systems. At the heart of this evolution are digital twins, embodied AI and generative AI-based robotics methods. These notions will change not only the robots's interactions with its physical environment, but also how they learn and adapt (Pastor-Escuredo et al., 2024; Siciliano & Khatib, 2016). Especially in the context of embodied AI, ideas like sim-to-real transfer, task-wise evaluation and online adaptation have emerged as central axes of (modern) robotics research (Duan et al., 2022).

Digital Twins: Fusing the Physical and Virtual World

The concept of a digital twin corresponds to a highly detailed simulation, of such a physical system in a virtual space, updated constantly with information from the real-world. In the context of robotics, digital twins are utilized for dynamic simulation to create a virtual model reflecting the status of a robot by combing sensor readings, operation models and system state information (Rakholia et al., 2024). Such a methodology enables a single "closed-loop" life cycle to combine design, testing, deployment, and maintenance of the robotic systems (Siciliano & Khatib, 2016).

AI models are frequently trained on digital-twin platforms that miners then transfer over to real systems, so that unsafe or expensive learning can be achieved relatively risk free. In industrial robotics, digital twins are commonly applied for predictive maintenance, process improvement or fault prediction (Pastor-Escuredo et al., 2024). In surgical robotics, digital twins are used for preoperative planning and simulation, to ensure greater patient safety and quality of the intervention (Tasdemirci et al., 2026).

The digital-twin concept also provides a learning and feedback capability that can be utilised to 'train' the robotic systems not only before they are deployed, but also once in service. Our approach is providing an early warning of performance variations, updating the parameters and tuning task strategies in a timely manner, which means achieving more robustness and continuity in autonomous system (Lu, 2021; Pastor-Escuredo et al., 2024). From the perspective of embodied AI, digital twins are situated as a systematic approach to bridging the sim-to-real gap (Duan et al., 2022).

Physical Embodied AI: Intelligence Shall Be Everywhere

Embodiment in AI is an ideal that advocates that AIs should learn or decide through interacting with the world via a body. From this viewpoint Intelligence is not a computational phenomenon in a narrow sense but as an attribute that results from the coordination of perception, action, and the environment (Nilsson, 1997). Robots are the closest examples of instantiations and manifestations of embodied AI (Siciliano & Khatib, 2016).

Robots designed in embodied AI produced conceptual knowledge through occupancy of the environment and slabbed it by comportment. Reinforcement learning, sensorimotor integration and task-based evaluation are the main learning and evaluation methodologies of embodied AI systems (Duan et al., 2022; Lu, 2021). This method is highly adaptable and flexible in tasks such as autonomous navigation, manipulation or human–robot interaction (Franceschetti, 2018; Siciliano & Khatib, 2016).

Meanwhile, as embodied AI intends to address the shortcomings of simulative-only learning with incorporation of real-world complexity into learning directly, it also brings about greatly increased challenges for safety , generalization and robustness under out-of-distribution (OoD) settings. Consequently, physical AI systems are often interoperated with digital twins and simulation environment, relying on safe learning and risk mitigating techniques (Amodei et al., 2016; Pastor-Escuredo et al., 2024).

Generative Robotics: Generative Models as a Design and Behavior-Planning Paradigm for Robot Task Planning, Motor Behavior, and Communication

The seamless combination of generative AI models, particularly large language models and network architectures, into robotic systems has led to the establishment of a new research direction called generative robotics. In this paradigm, robots are not just being commanded to following predefined sequences of behaviors but rather they can generate new plans and sequences of actions on the basis of task descriptions and environmental inputs (Klieštik et al., 2024; Kim et al., 2024).

Large language models provide advantages for robotics in natural language task specification, human-robot interaction, and multi-step planning. In particular, multimodal and embodied foundation models jointly learned visual perception together with linguistic representations to make more contextual aware and versatile decisions for task realization (Driess et al., 2023). The vision-language-action (VLA) effort poses new learning directions which bridge between web-scale knowledge and robotics control, and model actions in a joint representation space (Brohan et al., 2023). These advances not only improve natural-language interaction in service robots and human–robot based collaboration scenarios, but also reach the execution layer concerning task planning and step-by-step action generation (Kim et al., 2024; Tasneem & Pieters, 2026).

Generative methodologies render robotic systems more flexible and versatile, but also pose new challenges in terms of explainability, verifica- tion and reliability. A generative model that generates a believable but suboptimal plan may have catastrophic consequences in the real world. Hence, verification mechanisms, human in the loop and safe learning principles bear high relevance for generative robotics (Amodei et al., 2016; Yampolskiy, 2019).

Generative robotics is not restricted to behavioral synthesis but also includes the automatic optimization of robot morphology and control strategies, and generative models in this sense have been recently used for discovering other body shape designs and control policies in simulation (Hartl et al., 2025).

Integration, Limitations, and Future Perspectives

The simultaneously combined use of digital twins, personalized AI and generative robotics provides an environment for the evolution of AI-powered robotic systems that are increasingly autonomous, adaptive and sustainable. Yet this development also entails serious challenges (namely immense calculation efforts, privacy of data, incorrect or irrelevant plan generation and complex distributions between human agents and artificial systems (Abassi, 2019; Kim et al., 2024). For instance, when the decision-making process involves generative models, discussions about how human oversight can be preserved and who is to blame for harmful or incorrect outputs gain force (Russell, 2019; Yampolskiy, 2019).

For these reasons, the development of future robotics systems should not be viewed just as a matter of technical capability but within design frameworks that include safety-by-design principles and human-compatible objective setting, robust verification methods and suitable governance structures (Amodei et al., 2016; Russell, 2019). Other promising directions that could help in making practical this integrated vision are the use of digital-twin-based simulations as "safe testbeds", and embodied AI evaluations standardized through task-based metrics (Duan et al., 2022; Pastor-Escuredo et al., 2024).

Sustainability, Energy, and Carbon Dimensions

The rapid proliferation of AI-powered robots has not only brought about technological and economic change, but also profound implications on energy use, carbon release, and environmental stewa rdship. Robotic and AI technologies can increase the efficiency of production and services, for example, by optimizing resource consumption as well as increasing energy consumption owing to increased computational needs and a greater level of automation. Due to these two-fold impacts, it is imperative to consider a sustainability perspective when assessing AI-enabled robotics systems systemically (Ha, 2025; Kaack et al., 2022; Luo et al., 2026).

Energy Use of Robots & AI

The power consumption of AI-driven robotic systems includes two parts, (1) physical components (motors, sensors, actuators), and (2) computing hardware/software for data processing, model training, and inference. Indeed, training deep learning and large-scale AI models has been found to have very high energy consumption and carbon emissions (Ha, 2025). This situation calls for a combined consideration of "field energy" (specific to system motion/actuation) against "cloud/edge computing energy" (related to learning/inference) in robotic systems (Lu, 2021).

Meanwhile, robotics-based automation in production, logistics and maintenance can boost the energy efficiency of long-term processes. AI robot can be used to reduce the defect rate of the production line, material waste, and in addition through process optimization, it can also achieve production per unit output energy consumption down (Lu 2021). Thus, sustainability assessments need to account for immediate energy-related costs and long-term efficiency gains, as well as indirect side-effects like rebound effects in an integrated manner (Kaack et al., 2022).

Industrial Robots and Carbon Emissions

The influence of industrial robots on CO2 emissions has been the focus of intensive research in recent years. Based on spatial and temporal comparisons of energy consumption, industrial robots can realize the technological progress effects to reduce energy use and carbon emissions (Luo et al., 2026). Researching on the effect of AI development on carbon emissions also find that the direction and size of this effect is heterogeneous across sectoral composition, energy mix and technology diffusion dynamics (Yan & Sun, 2025).

But it is stressed that these effects differ in magnitude and direction from country to country. In robot intensive regions, material-intensive production drives up indirect energy requirements and sparks space overspillover on carbon emissions (Luo et al., 2026). These results indicate that the environmental impact of AI-powered robotic systems should be evaluated at hour, regional, and national level including the supply chain and energy infrastructures in place (Kaack et al., 2022).

Intelligent Robotic Systems and Energy Optimization

AI can also make robotics systems active agents in managing energy as opposed to just energy consumers. Smart robots could also usefully be used in energy demand forecasting, load balancing, and optimal storage of surplus generated electricity (Ha, 2025). When combined with robotic process automation, it can provide systemic value in areas such as smart grids, renewable energy integration and energy flexibility (Kaack et al., 2022).

AI-empowered systems in the field of agricultural and greenhouse robotics enable sustainable production models through improvement of processes such as irrigation, climate control and energy (Al-Najadi et al., 2025). Autonomous logistics and warehouse robots can similarly optimize travel path and schedule, and reasonably allocate resources; thenfollow it will also reduce fuel use, energy consumption (Lu, 2021). However, realization of net climate gain from these optimizations depends on carbon intensity of energy source and the scale of its deployment (Kaack et al., 2022).

AI and Robots: Advances in Carbon Emission Policy

AI-driven robotic systems to become common tools for carbon reduction. The accuracy and repeatability of robots on the factory floor can help in adopting low-carbon manufacturing technologies, while AI-based decision-support systems allow the reconfiguration of energy-intensive processes including the choices of more sustainable option (Ha, 2025; Kaack et al., 2022). At the same time, it is recognized that there could be a significant difference between “technical potential” and “realized impact” with relation to climate mitigation and that data access, incentive structures, regulation, and institutional capacity are crucial (Kaack et al., 2022).

On the other hand, the carbon emissions resulting from training and running AI models has moved to center stage in sustainability discussions. These existing solutions are thus instead pivoting towards energy-efficient algorithms, low-power hardware, edge/on-device inference strategies, and AI infrastructures harnessed with power generated from renewable sources (Ha, 2025; Luo et al., 2026). Furthermore, addressing safety and sustainability goals in a coagulated manner suggests that the environmental and social risks of autonomous systems should be contained within a unified design framework (Yampolskiy, 2019).

Policy, Governance, and Future Perspectives

The sustainability perspective of AI-driven robotic systems goes beyond technical solutions to include policy and governance aspects. Performance standards for energy-efficiency, carbon emissions regulations, incentives for green technologies and reporting requirements with regard to supply chains determine in a very direct manner the environmental impact of robotics and AI investments (Ha, 2025; Kaack et al., 2022). In this light, robotic system LCA methodologies and corporate carbon accounting may also become more important to be able to capture net emission effects (Kaack et al., 2022).

In the future, AI-enabled robotic systems are projected to be operated and designed according to carbon-neutrality. In this respect, sustainability is becoming a cornerstone as both robotic architectures and algorithms are designed to constraint the ecological footprint of robots with sustainable-aware algorithms, hardware selection or operational optimization (Lu, 2021; Ha, 2025).

Ethics, Safety, and Societal Impacts

The autonomy and proliferation of AI-based robotic systems are bringing new ethical, safety and societal impact discussions beyond the traditional techno-centric focus. Although robots are not alive and do not have values and intentions, they have moving parts and sensors that perceive (albeit not experience) the state of the world, learning processes that occasionally lead to successful action. They also make decisions — some in conjunction with human interlocutors while others comprise concrete intervention in matters of shared life between humans. As a result, robotic systems must be explained not only from an engineering point of view, but also in terms of the ethics, safety, and moral issues inherent to such technologies (Lu, 2021; Yampolskiy, 2019). The field of human-compatible AI specifically highlights that (1) systems should be aligned with human values, and (2) humans should maintain control—and so brings up robotics ethics to a more systemized level (Russell, 2019).

Ethical Issues and Responsibility Allocation

At one extreme end, the ethical stand-point can be framed as a question of autonomy and accountability in AI-based robotics. When robots act autonomously in this way, it becomes pertinent to ask who is morally and legally liable for the decisions that they make. Ethical consequences of robotic decisions are particularly relevant in the contexts where high-stakes decisions are made, such as healthcare, transportation and critical infrastructure (Yampolskiy, 2019; Russell, 2019).

In operative environments and surgical robotics, ethical considerations revolve around patient safety, informed consent and the nature of transparency in systems of decision-making. The prevailing model of AI-assisted surgical systems acting as primarily decision aids is based on a normative belief that ultimate authority should rest with human experts. This design option is motivated to avoid placing the entire ethical responsibility on

machines (Tasdemirci et al., 2026). When addressing the development of surgical robots with AI, discussion often emphasizes the tension between escalating autonomy and responsibility (Liu et al., 2024).

The ethics of data employed in robot learning is another hot topic. It can cause biases in datasets to result in unfair or discriminatory decisions made by robots. Hence, to assist with the construction of ethical robots, fairness, transparency and accountability need to be built into data collection, labeling and model training pipelines (Abassi, 2019; Lu, 2021).

Safety and Reliability

The safety in AI-based robotic system is a multidimensional concept, related to both cyber and physical domains. Physical security refers to reducing the potential of any form of damage in robot, human and environmental collaboration while cyber security means ensuring that robots are safe from malicious attack and unauthorized access (Abassi, 2019). As autonomous decision-making processes can make incorrect generalizations, out-of-distribution (OOD) or unpredictable behavior may occur, safe-learning and verification methods are also critical in reducing physical risks (Amodei et al., 2016; Yampolskiy, 2019).

Mistakes made in perception or decision modules of autonomous robots, may end up causing a dangerous safety issue like, for example, a collision, an unconvenient intervention or the failure of an essential task. Consequently, safe learning, fault tolerance, redundancy and human-in-the-loop control are now inherent features of modern robotics architectures (Lu, 2021). For robotic systems operating in critical infrastructures, it is especially imperative that decision-making processes remain both traceable and verifiable afterwards (Santoso & Finn, 2024).

From a cyber security standpoint, more connectivity in robots means a larger attack surface. For instance, taking control of AI-based robots, by either distorting their sensor readings or their decisions, could give rise to threats beyond simple risks to individual people and may instead represent danger for the society as a whole. Thus, security must be considered early in the life cycle of a system and safety by design principles as well as security by design approaches should be applied jointly (Yampolskiy, 2019).

Human–Robot Interaction and Societal Acceptance

The societal impacts of AI-driven robotic systems are closely tied to the quality of human–robot interaction. As service and social robots become more visible in everyday life, questions of user acceptance and long-term adoption gain prominence (Vanderborght, 2020). The integration of large language models enables service robots to engage in more natural language interaction, but it also requires reconsideration of risks such as misinformation, misleading responses, and user manipulation in the context of human–robot interaction (Kim et al., 2024; Russell, 2019).

Acceptance in society is not based solely on the technology performance of robots, but also on how predictable, explainable and socially acceptable their behaviors are. Social Acceptability: overgeneralizing We create social interfaces Attending to cultural norms, privacy and user preferences. Thus the social robotics is a multi-discipline research activity that requires integrating into it with intercultural design principles, privacy concerns and interaction norms (Papadopoulos et al., 2022).

Social robots that can teach, care for the elderly and act as rehabilitation aids, have great potential to offer social support and provide cognitive/emotional engagement. Yet, replacing human relationships so thoroughly with machine interaction raises ethical considerations around social isolation, emotional reliance, and the invisibility of care work (Lu 2021; Russel 2019).

Workforce, Economic, and Social Transformation

The rapid deployment of AI-powered robotic systems is causing a structural reshaping of labor markets. Although automation results in the disappearance or transformation of some jobs, it also creates new jobs and disciplines. Balancing the societal impact of robotics and AI is an important policy problem (Lu, 2021; Pastor-Escuredo et al., 2024).

Industrial robots can help to not only improve productivity but also cut down the production cost, and make region's economy more competitive. Meanwhile, it could push employment lower, especially for low- and medium-skilled workers. 27 These trends point to the need for reskilling, upskilling, and lifelong learning policies to minimize negative impacts (Pastor-Escuredo et al., 2024). Technological change must also be met with commensurate measures in education, social protection, and regional development if our rising inequality is to be stemmed (Lu, 2021).

Ethical Governance and Regulatory Frameworks

To ensure that AI-based robotic systems are designed and used in an ethical- and safe-by-design way, strong governance mechanisms and context-specific regulation need to be created. National and international AI ethics principles are intended to inform the design, development, and use of robots (Yampolskiy, 2019). For these principles to have practical impact they need to be transformed into engineering practices that engineers, policy makers or ethicists can directly operate with in their daily work; such as design checklists, risk assessments, validation and verification protocols, incident reporting instructions and sector-specific standards (Amodei et al., 2016; Abassi, 2019).

In this environment, explainable AI, user-centered design and responsibility are becoming touchstones of future robotic systems. "The additional capacity to establish and monitor the ethical governance mechanisms that are in place is essential if we are to promote public trust and facilitate sustainable adoption of AI-powered robotic technologies" (Russell, 2019; Abassi, 2019).

Future Perspectives and Conclusion

Nowadays, AI-based robotic systems are not anymore just technological tools that execute pre-specified tasks, they turn into complex sociotechnical systems able to learn, decide and adapt through continuous interaction with the environment. This shift has pushed a paradigmatic redefine of technical and application areas in robot field. As articulated in the earlier sections, the architectural (Lu, 2021) and algorithmic underpinnings (Pastor-Escuredo et al., 2024; Siciliano & Khatib 2016), as well as application domains, of robotics have been evolving towards broader and more dynamic solutions due to the merging of digital twins, embodied AI, and generative model s. The embodied AI literature argues that this transition cannot be attributed to "better algorithms" alone, and is heavily reliant on system-wide considerations including sim-to-real (simulation-to-reality transfer), task-based evaluation, generalization, and safe learning (Duan et al., 2022; Amodei et al., 2016).

Future Directions: From Autonomy to Collaboration

One important future trend of the AI-based robots is moving from the development fullautonomous robot to approaches which focus on human-robot cortina boration as can be seen. In fields, including but not only limited to healthcare, education, and service, treating robots as systems which assist rather than substitute human experts is being considered a more sustainable route from both ethical and practical aspects (Tasdemirci et al., 2026; Liu et al., 2024). This orientation is motivated by the goal of mitigating risks related to autonomous systems, maintaining human oversight and accountability (Yampolskiy, 2019; Russell, 2019).

Large language models and generative AI can be integrated into robotics to have robots accept task specifications in natural language and act contextually (Kim et al., 2024). While natural language can foster operator–robot interaction on the factory floor, concerns with data privacy and regulatory pressure further drive local (offline) deployment of generative models in closed-loop robotic scenarios (Tasneem & Pieters, 2026). On the other hand, VLA (vision-language-action) and embodied multimodal base models pave new ways for porting web scale facts into robot control and multi-step task execution but pose challenges in terms of verification, safety and vulnerability to OOD (out-of-distribution)(Amodei et al., 2016; Driess et al., 2023; Brohan et al., 2023).

Hence, the reliability, verifiability and explainability of generative/LLM-based robots are envisioned as core issues in future research. Indeed, alignment and value consistency with USV are considered fundamental for preserving trust in robotic systems making autonomous decisions (Russell, 2019; Yampolskiy, 2019).

Sustainability and Energy-Aware Robotic Design

Yet another major consideration for the future is to design energy-efficient, carbon-neutral AI-based robotic systems. The increasing computing burden of AI models calls for a more strategic consideration of robotic system environmental impacts (Ha, 2025). Given the potential of AI to contribute to climate-change mitigation, its net impact will depend on factors such as the context in which it is employed, the energy mix in which it operates,

rebound effects and governance capacity; thus technical potential does not necessarily translate into climate benefits (Kaack et al., 2022).

Spatial-econometric research on the positive and negative impacts of industrial robots on carbon emissions has also emphasized the necessity to combine robotic transition with sustainability policy-making (Luo et al., 2026). In a related vein, studies which looked into the effects of AI development and industrial robot deployment on the carbon intensity levels across sectors suggested that they have the potential to influence sectoral C I, and direction and magnitude was contingent on how AI production and robots development diffuse over inter-sector (Yan & Sun, 2025). In this notion, future robotic systems will be designed with sustainable algorithms, hardware of low energy consumption and infrastructure powered by grid and renewable energy (Lu, 2021; Kaack et al., 2022).

Ethics- and Governance-Oriented Future Approaches

Progress in AI-based robotic systems as well as ethical governance and regulatory developments will define the future of industry. Ensuring transparency and accountability in the operation of autonomous systems is a necessary components towards maintaining societal trust in AI (Abassi, 2019; Russell, 2019; Yampolskiy, 2019). The AI safety literature emphasizes that safety is higher-order than principles: it must be translatable into engineering practices, such as testing, verification, safe learning, incident reporting and attack-surface reduction (Amodei et al., 2016).

Given the direct intersection of cyber security and physical safety in networked robotic systems, such that compromises to one are tantamount to anachronistic notionuits to the other, future robotic architectures will incorporate security-by-design and safety-by-design in concert (Santoso & Finn, 2024). In social robotic and in health domains, the importance of cultural context for user expectations is crucial for privacy, trust and society acceptance (Papadopoulos et al., 2022). Consequently, it is expected that the research will see to medium-term institutionalization of the human-centered and ethics-by-design robot-system development approaches (Papadopoulos et al., 2022; Russell, 2019).

Conclusion

This chapter has presented AI-enabled robotics systems in a holistic manner that covers their conceptual underpinning, architectural design, algorithmic techniques, application domain aspects, sustainability views as well as ethical–societal issues. The literature surveyed here reflects a trend towards more autonomous, learning, and adaptive robotics, although this means that along with technical improvements there come also ethical as well as environmental and social responsibilities (Lu, 2021; Pastor-Escuredo et al., 2024; Kaack et al., 2022).

Finally, we will be approaching the meaning of the future in terms of both interdisciplinary collaboration and integral evaluation in AI-driven robotics. The historical dichotomy points at the need to be shaping not only increased functioning and performance of our robots,r but also systems with which humans can live, sustainable technologies, and ethically aligned machines which share in the long term success of the field (Russell 2019;

Yampolskiy 2019). In this way contract-based AI robotic systems are more than just the drivers of technosocial change, they are also agents of wider social and institutional transformation (Papadopoulos et al., 2022).

Disclosure of AI usage

During the preparation of this work, the author(s) used [OpenAi-ChatGPT and Google Gemini] in order to [e.g., generate text, check grammar, analyze data, or assist with literature search]. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the published work.

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Chapter 2- Artificial Intelligence Applications in Healthcare

Muhammed Coşkun Irmak

Chapter Highlights

- Artificial intelligence has become a transformative force in healthcare, impacting diagnosis, treatment planning, patient monitoring, and clinical decision-making processes.
- Machine learning and deep learning techniques enable data-driven, personalized, and predictive healthcare solutions by leveraging medical images, electronic health records, biosignals, and multimodal data sources.
- AI-based clinical decision support systems enhance diagnostic accuracy and operational efficiency while maintaining the central role of human expertise in medical practice.
- Predictive analytics and anomaly detection approaches play a critical role in early disease detection, risk stratification, and proactive patient care management.
- Ethical, legal, and security considerations—such as data privacy, transparency, accountability, and regulatory compliance—are fundamental to the responsible deployment of AI in healthcare.
- The future of AI in healthcare lies in explainable, human-centered, and supervised autonomous systems that support clinicians while ensuring trust, safety, and sustainability.

Introduction

Healthcare services have undergone a profound digital transformation in recent years, driven by rapid advances in information and communication technologies. The widespread adoption of electronic health records (EHRs), advancements in medical imaging technologies, and the continuous generation of patient data through biosensors and wearable devices have collectively created an unprecedented data ecosystem in the healthcare domain. While this transformation aims to make healthcare services more accessible, efficient, and patient-centered, it has also significantly increased the complexity of clinical decision-making processes. The growing volume and heterogeneity of healthcare data challenge the limits of traditional analytical methods and clearly reveal the need for more advanced, automated, and learning-based systems.

In this context, artificial intelligence (AI) has emerged as one of the key driving forces behind the digital transformation of healthcare. AI subfields such as machine learning (ML), deep learning (DL), and big data analytics offer unique capabilities for analyzing complex healthcare data, discovering clinically meaningful patterns, and enhancing decision support processes. The literature emphasizes that the application of AI in healthcare is not limited to improving diagnostic accuracy; rather, it is transforming a wide range of critical processes, including early disease detection, risk prediction, treatment planning, and healthcare resource management (Topol, 2019; Esteva et al., 2019).

Traditional healthcare delivery has largely relied on physician expertise and rule-based clinical protocols. However, the growing diversity of patient populations, the prevalence of multimorbidity (comorbid conditions), and the increasing demand for individualized treatment strategies in modern healthcare systems often render these approaches insufficient. AI-based systems enable the construction of individualized risk profiles and the development of personalized medicine approaches by learning from large-scale patient data. In this respect, AI is regarded as a strategic technology that supports the transition from “one-size-fits-all” practices toward patient-centered and data-driven decision-making mechanisms in healthcare services (Rajkomar et al., 2019).

In recent years, the success of DL-based models has accelerated the widespread adoption of AI applications, particularly in the field of medical imaging. AI systems developed in domains such as radiology, pathology, dermatology, and ophthalmology have demonstrated performance levels comparable to, or in some cases approaching, those of expert clinicians for specific tasks (Litjens et al., 2017; Gulshan et al., 2016). Nevertheless, the impact of AI in healthcare is not confined to diagnostic processes alone. Areas such as clinical workflow optimization, hospital operations management, patient monitoring systems, and telehealth services are increasingly benefiting from AI-driven solutions.

However, the widespread adoption of AI in healthcare has also given rise to significant ethical, legal, and security-related concerns. Issues such as patient privacy, data protection, algorithmic bias, and clinical accountability are of critical importance for the trustworthiness of AI-enabled healthcare systems. Therefore, the evaluation of AI applications in healthcare should not be limited to technical performance metrics alone; it must also consider ethical principles, legal regulations, and societal acceptance frameworks (Floridi et al., 2018).

The aim of this chapter is to examine the use of AI in healthcare from a holistic perspective and to evaluate current developments in light of contemporary academic literature and clinical practice. Within this scope, the chapter addresses the structure of healthcare data, diagnostic and clinical decision support systems, medical imaging applications, intelligent healthcare systems, as well as ethical and legal considerations. In doing so, it seeks to provide readers with a comprehensive and balanced framework for understanding the current state and future potential of AI in the healthcare sector.

Healthcare Data and AI Infrastructure

The success of AI-based healthcare applications largely depends on the quality, diversity, and proper processing of the data used. The healthcare domain represents one of the most complex data ecosystems, characterized by heterogeneous, multi-source, and high-dimensional data generation. EHRs, medical images, biosignals, laboratory results, genomic data, and patient-generated data together constitute a rich yet challenging infrastructure for AI models. Consequently, AI applications in healthcare require not only the development of advanced algorithmic models but also a holistic infrastructure approach that encompasses data collection, integration, preprocessing, and secure data management.

EHRs constitute one of the primary data sources for AI applications in healthcare (Fig. 1). EHR systems contain both structured and unstructured data, including patient demographic information, diagnoses, medications, laboratory results, and clinical notes. These data form the foundation of numerous AI-driven applications, such as clinical decision support systems, risk prediction, and disease prognosis modeling. However, the heterogeneity, incompleteness, and variability of standards across healthcare institutions pose significant challenges to the generalizability of AI models (Rajkomar et al., 2018). As a result, data preprocessing, normalization, and interoperability solutions have become indispensable components of AI infrastructure in healthcare.

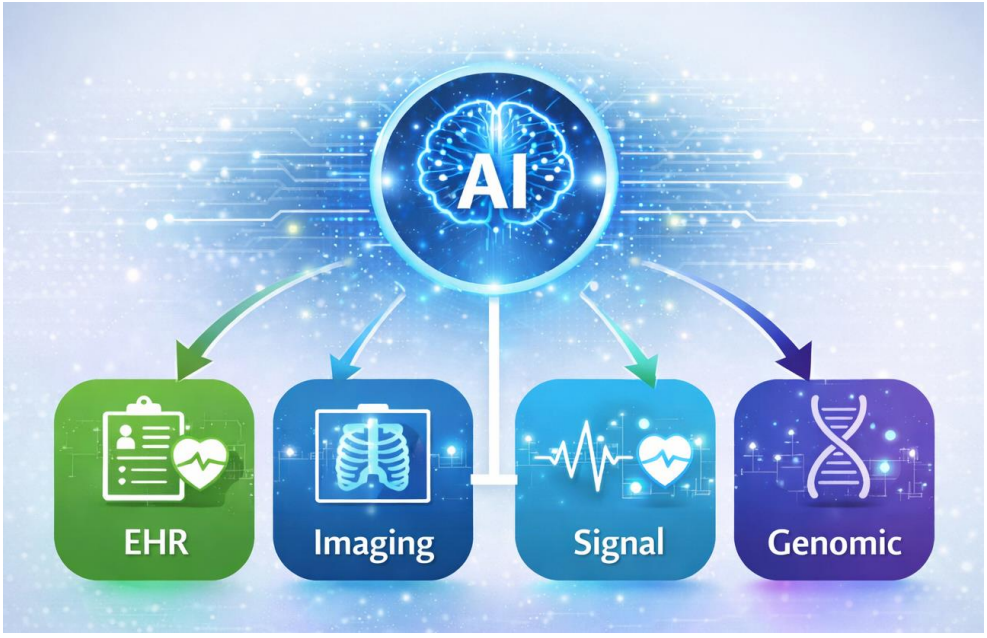

Figure 1. Types of Healthcare Data and Their Interaction with AI

Medical imaging data represent one of the most extensively and successfully utilized data types in AI-driven healthcare applications. Imaging modalities such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound generate high-dimensional and visually rich data. DL–based convolutional neural networks (CNNs) have demonstrated high performance in tasks such as classification, segmentation, and lesion detection by learning complex spatial patterns from medical images (Litjens et al., 2017). Nevertheless, the requirement for expert-level annotation and the associated high costs constitute major limitations in the development of large-scale labeled medical imaging datasets.

Biosignals—such as electrocardiography (ECG), electroencephalography (EEG), and electromyography (EMG)—along with time-series data obtained from wearable devices enable continuous monitoring of patients' physiological states. These data types are widely used in early warning systems and disease progression prediction, particularly in cardiology, neurology, and rehabilitation contexts. Models based on DL and time-series analysis are capable of capturing complex and nonlinear patterns in biosignals, often achieving higher accuracy than traditional analytical approaches (Shickel et al., 2018). However, sensitivity to noise and inter-device measurement variability remain critical challenges that must be carefully addressed to ensure model reliability.

Genomic and other omics data—such as transcriptomics, proteomics, and metabolomics—constitute important data sources that strengthen the role of AI in personalized medicine approaches. These data offer substantial potential for understanding the molecular basis of diseases, predicting treatment responses, and developing individualized therapeutic strategies. However, the high dimensionality of genomic data, limited sample sizes, and associated ethical sensitivities pose significant technical and legal challenges for AI applications in this domain (Libbrecht & Noble, 2015).

Another critical dimension of AI infrastructure in healthcare is data integration and interoperability. The integrated analysis of heterogeneous data sources—including clinical records, medical images, biosignals, and genomic data—enables the development of more comprehensive and reliable clinical decision support systems. Multimodal learning approaches address these diverse data types within a unified modeling framework, thereby improving accuracy and generalizability in healthcare applications (Huang et al., 2020). The main types of healthcare data, the AI methods applied to these data, and their corresponding clinical use cases are summarized in Table 1.

Finally, data security and privacy constitute indispensable components of AI infrastructure in healthcare. Given that healthcare data contain highly sensitive personal information, data storage, sharing, and processing processes must be supported by robust security mechanisms. In this context, approaches such as federated learning, privacy-preserving ML, and encrypted data analytics offer promising solutions by enabling the training of AI models without the need for centralized data sharing (Rieke et al., 2020).

Table 1. Types of Healthcare Data, AI Methods, and Clinical Use Cases

Healthcare Data Type	AI Methods Used	Primary Clinical Application Areas	Representative Literature
EHRs	ML, DL, natural language processing (NLP)	Clinical decision support systems, disease risk and prognosis prediction, patient stratification	Rajkomar et al. (2018); Shickel et al. (2018)
Medical Imaging (X-ray, CT, MRI, US)	CNNs, DL, transfer learning	Diagnostic support systems, lesion detection, segmentation, radiology and pathology applications	Litjens et al. (2017); Esteva et al. (2019)
Biosignals (ECG, EEG, EMG, etc.)	Time-series analysis, recurrent neural networks (RNNs), long short-term memory (LSTM), DL	Early warning systems, arrhythmia detection, neurological disorder analysis, remote patient monitoring	Faust et al. (2018); Hannun et al. (2019)
Wearable Device Data	ML, anomaly detection, time-series models	Continuous patient monitoring, lifestyle analysis, chronic disease management	Dunn et al. (2021); Smuck et al. (2021)
Genomic and Omics Data	DL, dimensionality reduction, statistical learning	Personalized medicine, treatment response prediction, disease risk analysis	Libbrecht & Noble (2015); Zou et al. (2019)
Multimodal Data Sources	Multimodal DL, data fusion, attention-based models	Comprehensive clinical decision support systems, complex disease analysis	Huang et al. (2020); Baltrušaitis et al. (2019)

Diagnosis, Prediction, and Clinical Decision Support Systems

Diagnostic and clinical decision-making processes are among the most critical components of healthcare services, as errors at these stages directly affect patient safety and treatment outcomes. In traditional clinical practice, diagnostic and therapeutic decisions are largely shaped by physicians' knowledge base, clinical experience, and guideline-based protocols. However, the rapid increase in patient volume, the growing prevalence of complex and multimorbid conditions, and the substantial expansion of clinical data in terms of volume, variety, and velocity have made the limitations of these traditional approaches increasingly evident. In this context, AI-driven diagnostic and decision support systems have emerged as strategic tools that enhance and complement clinical decision-making processes.

AI-based diagnostic systems aim to identify disease-specific patterns by learning from large-scale and high-dimensional patient data. ML and DL approaches can improve diagnostic accuracy by integratively analyzing heterogeneous data sources, including laboratory results, clinical notes, biosignals, and medical images. In particular, DL–based models demonstrate superior performance beyond traditional statistical methods due to their capacity to learn complex and nonlinear relationships. The literature reports that AI systems developed in fields such as dermatology, radiology, and pathology have achieved performance levels comparable to, or in some cases equivalent to, those of expert clinicians for specific diagnostic tasks (Litjens et al., 2017; Esteva et al., 2019). While these advances highlight the significant potential of AI in diagnostic processes, they do not diminish the indispensable role of clinical context and physician judgment.

Beyond diagnostic processes, another important application area of AI in healthcare involves prediction-based approaches. Outcomes such as disease onset risk, likelihood of clinical deterioration, need for intensive care, length of hospital stay, and mortality can be predicted in advance using historical patient data. Such predictive models provide healthcare professionals with critical time advantages, particularly in clinical situations requiring early intervention. Rajkomar et al. (2019) demonstrated that DL–based models are capable of simultaneously predicting multiple clinical outcomes and achieving higher accuracy in clinical risk assessment compared to traditional methods. This capability facilitates a transition in healthcare from reactive approaches toward proactive and preventive strategies.

Clinical decision support systems (CDSS) are structures that enable the integration of AI-based diagnostic and predictive models into clinical workflows. CDSS provide patient-specific alerts, recommendations, and risk assessments, thereby supporting physicians' decision-making processes. While early CDSS implementations were largely based on rule-based systems, contemporary approaches have evolved into ML–driven, adaptive, and continuously learning systems (Fig. 2). Modern CDSS frameworks can update their models with new patient data over time, leading to improved performance and better alignment with real-world clinical environments (Sutton et al., 2020).

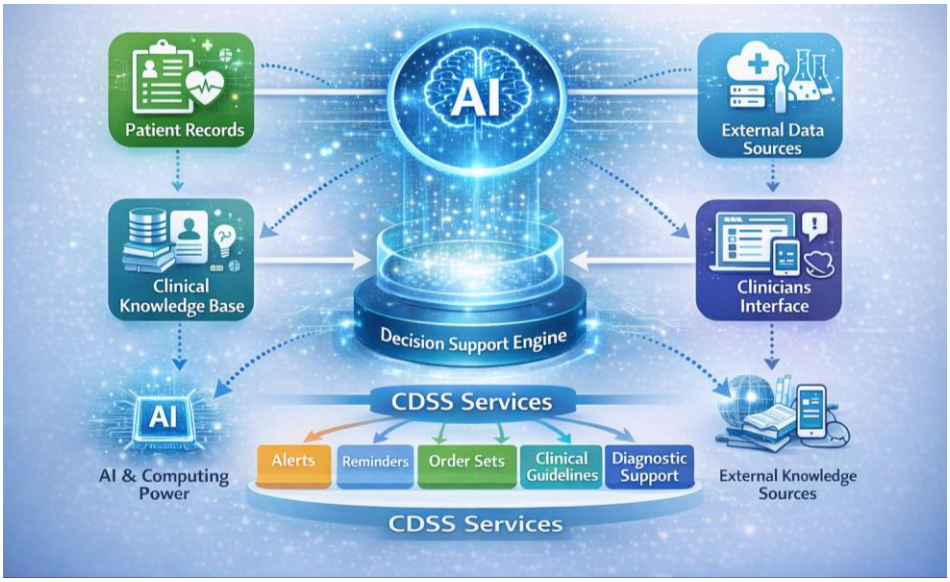

Figure 2. Clinical Decision Support Systems Architecture

Nevertheless, the success of CDSS cannot be assessed solely on the basis of model accuracy. The literature provides evidence that some AI models exhibiting high technical performance have yielded limited impact in real-world clinical practice. Key factors underlying this gap include challenges in integration with clinical workflows, inadequate user interface design, lack of clinician trust in the system, and issues related to explainability (Sendak et al., 2020). In particular, models perceived as “black boxes” tend to be approached with caution by clinicians and are often used in a limited manner during clinical decision-making processes.

At this point, explainable artificial intelligence (XAI) approaches emerge as a critical component in increasing the acceptance of CDSS. XAI methods enable clinicians to understand how a model arrives at a specific diagnostic or predictive outcome by providing transparent explanations of the underlying decision mechanisms. Especially in high-risk clinical decision scenarios, explainability is of paramount importance from both ethical and legal perspectives (Arrieta et al., 2020). Explainable models strengthen physician–AI collaboration and enhance the overall trustworthiness of these systems.

In summary, AI-based diagnostic, predictive, and CDSS hold significant potential to improve accuracy, efficiency, and effectiveness in healthcare services. However, for these systems to be sustainably and reliably integrated into clinical practice, factors such as human-centered design, explainability, ethical alignment, and seamless integration with clinical workflows must be addressed alongside technical performance. This holistic approach forms the foundation for positioning AI as a supportive and trustworthy decision partner in healthcare.

Medical Imaging and Intelligent Clinical Applications

Medical imaging represents one of the most rapidly maturing subfields of AI applications in healthcare and one of the areas most extensively integrated into clinical practice. High-resolution images generated in disciplines such as radiology, pathology, dermatology, and ophthalmology play a central role in diagnosis, treatment planning, and disease monitoring processes. With advances in imaging technologies, the increasing volume of generated data has made manual image interpretation progressively more challenging, thereby substantially amplifying the need for automated analytical solutions. In this context, DL–based AI approaches provide powerful and scalable solutions for the analysis of medical images.

CNNs are among the most widely used DL architectures in medical image analysis. CNN-based models are capable of achieving high accuracy in fundamental tasks such as classification, segmentation, and lesion detection (Fig. 3). Comprehensive reviews in the literature demonstrate that CNN-based approaches have yielded successful results, particularly in the detection of lung diseases, breast cancer, brain tumors, and retinal pathologies (Irmak et al., 2022; Litjens et al., 2017). Transfer learning strategies partially address the challenge of limited labeled medical data by enabling the adaptation of pretrained models to domain-specific clinical datasets.

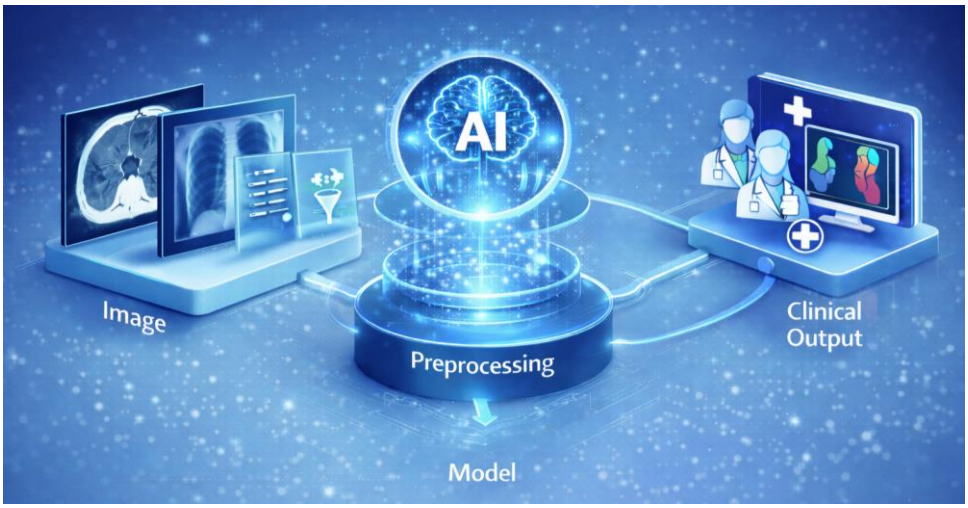

Figure 3. AI-Based Analysis in Medical Imaging

One of the most significant contributions of AI in medical imaging is its support for standardizing diagnostic processes and reducing observer-dependent variability. In clinical practice, different experts may provide varying interpretations of the same image, leading to uncertainty in diagnostic decision-making. AI-driven systems can mitigate such variability by producing more consistent and reproducible results. Particularly in the field of pathology, DL models operating on digital whole-slide images have been shown to support expert pathologists in tasks such as tumor detection and grading (Campanella et al., 2019).

Medical imaging applications are not limited to diagnostic tasks; they also provide substantial contributions to treatment planning and disease monitoring processes. Segmentation-based models are employed in tasks such as tumor volume estimation, delineation of organ boundaries, and radiotherapy planning. These applications enable treatment processes to be conducted in a more precise and personalized manner. Furthermore, AI-driven systems facilitate more effective monitoring of disease progression and assessment of treatment response by comparing medical images acquired over time.

Advances in medical imaging have also paved the way for the emergence of intelligent clinical applications. Intelligent clinical applications are systems designed to integrate AI-based analyses into clinical workflows. The joint evaluation of imaging analysis results with CDSS provides clinicians with more comprehensive and context-aware information. For instance, analyzing radiological findings in conjunction with patient history, laboratory results, and biosignals contributes to more accurate and holistic clinical decision-making. The main medical imaging modalities, the AI methods commonly applied to these modalities, and their clinical application areas are summarized in Table 2.

Another important component of intelligent clinical applications is their integration with telehealth services and wearable technologies. Physiological data collected through wearable devices and sensors can be continuously monitored by being evaluated in conjunction with medical imaging results. This approach offers significant advantages, particularly in areas such as chronic disease management and postoperative patient follow-up. The literature reports that such integrated systems contribute to reductions in hospital admission rates and improvements in patient satisfaction (Topol, 2019).

Table 2. Medical Imaging Modalities, AI Methods, and Clinical Applications

Imaging Modality	AI Methods Used	Primary Clinical Applications	Representative Literature
X-ray	CNNs, transfer learning, DL	Detection of pulmonary diseases, pneumonia and COVID-19 diagnosis, bone fracture analysis	Litjens et al. (2017); Esteva et al. (2019) Irmak et al. (2022)
CT	CNNs, U-Net, 3D DL	Lung nodule detection, tumor segmentation, organ analysis	Litjens et al. (2017); Topol (2019)
MRI	CNNs, recurrent neural networks (RNNs), multi-scale DL	Brain tumor analysis, neurological disorders, soft tissue segmentation	Campanella et al. (2019); Rajkomar et al. (2019)
Digital Pathology (Whole-Slide Imaging, WSI)	CNNs, multi-scale networks, attention mechanisms	Cancer detection, tumor grading, pathological classification	Campanella et al. (2019); Litjens et al. (2017)
Ultrasound (US)	CNNs, real-time DL	Fetal imaging, cardiac function analysis, musculoskeletal assessment	Esteva et al. (2019); Sutton et al. (2020)
Ophthalmic Images	CNNs, DL	Detection of diabetic retinopathy, glaucoma, and macular degeneration	Gulshan et al. (2016); Topol (2019)

Nevertheless, the widespread use of AI in medical imaging and intelligent clinical applications also introduces several technical and ethical challenges. Issues such as model generalizability, biases in datasets, variability across imaging devices, and the lack of explainability must be carefully addressed to ensure clinical reliability. In particular, models perceived as “black boxes” tend to receive limited acceptance in clinical decision-making processes, with clinicians approaching these systems cautiously. Therefore, integrating explainable AI approaches into medical imaging applications is of critical importance for enhancing clinical acceptance and trust (Arrieta et al., 2020).

In conclusion, medical imaging and intelligent clinical applications represent some of the most tangible and impactful use cases of AI in healthcare. Advances in this domain not only improve diagnostic accuracy but also optimize clinical workflows, thereby strengthening the effectiveness and sustainability of healthcare services. However, for this potential to be realized in a reliable and ethical manner, technical achievements must be considered alongside clinical context, human-centered design principles, and regulatory frameworks.

Ethics, Security, and Data Privacy

The widespread adoption of AI applications in healthcare brings not only substantial clinical benefits but also significant ethical, security, and data privacy challenges. Healthcare data contain highly sensitive personal information; therefore, their processing, sharing, and interpretation by automated systems require a high level of responsibility. Consequently, the success of AI applications in healthcare should be evaluated not solely on the basis of technical performance metrics, but also in terms of compliance with ethical principles, security robustness, and legal regulations.

From an ethical perspective, one of the most fundamental challenges in AI-enabled healthcare systems is the issue of fairness and bias. AI models tend to learn patterns and biases embedded in the datasets on which they are trained. If training data do not adequately represent certain patient groups, the resulting models may produce inaccurate or unfair outcomes for specific demographic populations. The literature reports that imbalances in data related to gender, age, and ethnicity can lead to systematic errors in CDSS (Obermeyer et al., 2019). This reality underscores the necessity of continuous ethical monitoring and evaluation of AI applications in healthcare.

Another critical ethical dimension concerns the principles of explainability and transparency. Although many DL–based AI models achieve high levels of accuracy, they are often perceived as “black boxes.” In clinical practice, it is of paramount importance for physicians to understand the rationale behind a diagnostic or treatment recommendation. XAI approaches aim to enhance clinicians’ trust in AI systems by revealing the underlying reasons for model outputs (Arrieta et al., 2020). Explainability also plays a crucial role in the distribution of legal and ethical responsibility associated with AI-supported clinical decisions.

The security dimension constitutes another fundamental component of AI applications in healthcare. AI-based systems not only influence clinical decision-making but also become potential targets for cyberattacks. Threats such as data poisoning, adversarial attacks, and model reverse engineering can undermine the reliability of AI systems. In particular, studies have demonstrated that small and imperceptible input perturbations in medical imaging systems can lead to significant changes in model outputs (Finlayson et al., 2019). Therefore, AI applications in healthcare must be supported by model-specific security strategies that go beyond conventional information security measures.

Data privacy constitutes one of the most sensitive and highly regulated dimensions of AI usage in healthcare. The processing of healthcare data is subject to strict legal frameworks in many countries. In Türkiye, the Personal Data Protection Law (KVKK, Law No. 6698), in the European Union, the General Data Protection Regulation (GDPR), and in the United States, the Health Insurance Portability and Accountability Act (HIPAA) establish the primary legal frameworks for the protection of healthcare data. These regulations mandate fundamental principles such as data minimization, informed consent, purpose limitation, and secure data processing. The main data protection regulations that directly affect AI applications in healthcare, along with their core principles, are summarized in Table 3.

In this context, privacy-preserving learning approaches are gaining increasing importance as alternatives to AI models that rely on centralized data sharing. Federated learning enables the training of local models and their aggregation into a global model without requiring data from different institutions to be pooled in a central repository. This approach not only safeguards data privacy but also promotes inter-institutional collaboration (Rieke et al., 2020). Similarly, techniques such as differential privacy and homomorphic encryption offer promising solutions for protecting sensitive healthcare data while enabling advanced AI-driven analytics.

Finally, it should be emphasized that ethical and security considerations are not the sole responsibility of technical teams. The reliable and sustainable deployment of AI applications in healthcare requires multidisciplinary collaboration among clinicians, data scientists, software developers, legal experts, and policymakers. In the literature, this approach is addressed within the framework of responsible artificial intelligence, which is recognized as a fundamental principle for developing ethical, secure, and human-centered AI systems in the healthcare domain (Floridi et al., 2018; Jobin et al., 2019).

Table 3. Major Data Protection Regulations and Core Principles for AI Applications in Healthcare

Regulation	**Scope / Region**	**Primary Objective**	**Key Principles Relevant to AI in Healthcare**
Personal Data Protection Law (KVKK, Law No. 6698)	Türkiye	Protection of individual rights in the processing of personal data	Informed consent, data minimization, purpose limitation, strict protection of special categories of personal data (health data)
General Data Protection Regulation (GDPR)	European Union	Strengthening individuals' control over their personal data	Lawfulness, transparency, data minimization, explainability, right to object to automated decision-making
Health Insurance Portability and Accountability Act (HIPAA)	United States	Ensuring the privacy and security of health information	Protection of Protected Health Information (PHI), access control, data security, audit mechanisms
AI Ethics Guidelines (General Framework)	International	Development of trustworthy and responsible AI	Fairness, prevention of discrimination, explainability (XAI), accountability, human oversight
Institution-Specific Healthcare Policies	Institution / Country-specific	Clinical safety and patient privacy	Data anonymization, model validation, shared clinical responsibility

Academic and Clinical Application Examples

The maturity of AI applications in healthcare is evaluated not solely through theoretical model performance, but also through real-world implementations that extend from academic research to clinical practice. In this context, academic studies enable the testing of novel methods under controlled and reproducible conditions, whereas clinical applications demonstrate the scalability, reliability, and tangible contributions of these methods to patient care. The literature emphasizes that progress in AI-driven healthcare has been largely fueled by the interaction between these two ecosystems.

In academic research, AI-based healthcare applications are predominantly focused on model development and evaluation targeting specific clinical problems. Studies conducted in the field of medical imaging provide some of the most prominent examples of this approach. DL–based models have achieved high levels of accuracy across a wide range of applications, including lung diseases, various cancer types, and retinal pathologies. In particular, models trained on large-scale datasets have been shown to produce performance levels comparable to those of expert clinicians for specific diagnostic tasks (Litjens et al., 2017; Gulshan et al., 2016). These studies provide important academic evidence demonstrating that AI can be utilized as a supportive tool in clinical diagnostic processes.

Academic research in the field of clinical prediction and risk assessment has also produced notable results. The early prediction of clinical deterioration in intensive care units, sepsis early warning systems, and mortality prediction models are among the most extensively studied applications of AI-based approaches. Rajkomar et al. (2019) demonstrated that DL–based models are capable of simultaneously predicting multiple clinical outcomes and offer significant advantages in terms of early intervention. Such studies highlight that AI can be effective not only in diagnostic tasks but also in the management of clinical processes.

However, the translation of these academically developed methods into clinical practice introduces significant technical and organizational challenges. AI systems deployed in clinical environments are required to operate in real time, integrate seamlessly with heterogeneous data sources, and support clinical workflows without causing disruption. In response to these challenges, some healthcare institutions have begun to evaluate AI models developed in academic settings through pilot implementations in real-world clinical environments. For example, AI-assisted image analysis systems used in radiology departments provide preliminary assessments to clinicians, thereby reducing workload and accelerating diagnostic processes.

One of the most successful examples in clinical practice is the AI-based systems developed in the field of ophthalmology for diabetic retinopathy screening. These systems have increased early detection rates by reducing the need for specialist physicians during large-scale screening processes. Similarly, digital pathology systems developed in the field of pathology provide substantial support to clinicians in tumor detection and grading tasks (Campanella et al., 2019). Such applications offer concrete evidence that AI can be reliably integrated into clinical practice. Representative examples of academic AI-based studies in healthcare and their translation into clinical applications are summarized in Table 4.

Table 4. Representative Academic and Clinical Applications of AI in Healthcare

Application Domain	AI Methods Used	Academic Study / Approach	Clinical Impact and Application	Representative Literature
Radiology	CNNs, DL, transfer learning	Image classification and segmentation models for lung nodule and pneumonia detection	Reduced diagnostic time, decreased physician workload, improved diagnostic consistency	Litjens et al. (2017); Esteva et al. (2019)
Ophthalmology	CNNs, DL	Detection of diabetic retinopathy from retinal images	Early diagnosis in screening programs, reduced dependency on specialists	Gulshan et al. (2016)
Pathology (Digital Pathology)	Multi-scale CNNs, attention mechanisms	Digital slide analysis for tumor detection and grading	Increased diagnostic accuracy, accelerated pathology workflows	Campanella et al. (2019)
Intensive Care and Clinical Prediction	DL, time-series models	Prediction of clinical deterioration, sepsis, and mortality	Early warning systems, timely intervention, improved patient outcomes	Rajkomar et al. (2019)
Remote Patient Monitoring	ML, anomaly detection	Continuous data analysis from wearable devices	Chronic disease management, reduced hospital admission rates	Topol (2019); Shickel et al. (2018)
CDSS (CDSS)	ML/DL-based prediction and recommendation systems	Patient-specific risk assessment and treatment recommendations	Enhanced clinical decision-making, reduced error rates	Sutton et al. (2020); Sendak et al. (2020)

Nevertheless, the direct translation of academic achievements into clinical practice is not always feasible. This challenge, commonly referred to in the literature as the “last mile problem,” describes the gap between high-performing models developed in laboratory or experimental settings and their limited real-world impact in clinical environments. The primary factors contributing to this gap include differences in data distributions, challenges related to integration into clinical workflows, issues of user acceptance, and regulatory requirements (Sendak et

al., 2020). Therefore, academic–clinical collaborations should not be confined solely to the model development phase but should also encompass implementation, validation, and post-deployment evaluation processes.

In recent years, the strengthening of academia–clinical partnerships has enabled the more systematic and reliable deployment of AI-based healthcare applications. Multicenter studies facilitate model validation across diverse patient populations, thereby enhancing generalizability. Moreover, the increased involvement of regulatory authorities and ethics committees throughout the development and deployment lifecycle has contributed to improved clinical reliability and greater societal acceptance of AI-driven healthcare solutions.

In summary, the interaction between academic research and clinical practice plays a critical role in the maturation of AI applications in healthcare. While academic studies contribute innovative methods and theoretical depth, clinical implementations reveal the practical value and limitations of these approaches under real-world conditions. Addressing these two perspectives in an integrated manner forms the foundation for the sustainable and trustworthy adoption of AI technologies in the healthcare domain.

Future Perspectives and Conclusion

The rapid advancement of AI in the healthcare domain has created a broad impact ranging from diagnosis and treatment to care processes and the organization of health services. The studies and application examples discussed in this chapter demonstrate that AI has evolved beyond being merely an auxiliary tool in healthcare systems; it has become a strategic technology that strengthens clinical decision support processes, transforms clinical workflows, and promotes patient-centered approaches. Nevertheless, for this transformation to continue in a sustainable and trustworthy manner, several key future directions and inherent limitations must be carefully considered.

From a future-oriented perspective, AI applications in healthcare are expected to increasingly evolve toward multimodal data integration. The combined analysis of EHRs, medical images, biosignals, and genomic data will enable more comprehensive and personalized clinical decision-making. With the continued development of multimodal DL approaches, models relying on a single data source are likely to be replaced by more holistic and context-aware systems. This shift is expected to significantly enhance the clinical value of AI, particularly in the management of complex and multifactorial diseases.

Another important trend is the increasing adoption of the concept of supervised autonomy in healthcare. Fully autonomous AI systems face limited acceptance in clinical environments due to ethical, legal, and safety-related risks. Instead, hybrid systems that place physician oversight at the center and emphasize human–machine collaboration are expected to become more widespread. This approach combines the speed and analytical capacity of AI with human expertise, thereby offering solutions that are both more reliable and more acceptable in clinical practice.

The advancement of XAI also plays a critical role in shaping the future of AI in healthcare. Ensuring that the rationale behind clinical decisions is interpretable enhances clinicians' trust in AI systems and contributes to clearer definitions of ethical and legal responsibility. In the future, healthcare-oriented AI systems will be required not only to achieve high predictive accuracy but also to satisfy transparency and explainability criteria as fundamental design requirements.

Nevertheless, the widespread adoption of AI applications in healthcare is accompanied by several structural limitations. Issues related to data quality and data sharing, the lack of standardization across healthcare institutions, and variations in regulatory frameworks between countries complicate the scalability of AI-driven solutions. Moreover, the limited number of prospective studies evaluating the long-term clinical effectiveness of AI systems highlights the need for further research to better understand their impact on real-world patient outcomes.

In conclusion, while AI offers significant opportunities in the healthcare domain, the reliable and sustainable integration of this technology into clinical practice requires the simultaneous consideration of technical, ethical, and organizational dimensions. The analyses presented in this chapter aim to evaluate the current state and future potential of AI applications in healthcare within a holistic framework. The development of AI-enabled healthcare systems in accordance with human-centered design principles and the responsible AI paradigm will play a decisive role in improving the quality, safety, and accessibility of healthcare services.

Disclosure of AI usage

During the preparation of this work, the author used ChatGPT in order to generate text and check grammar. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published work.

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Chapter 3- Generative Artificial Intelligence, Gamification, and Interactive Learning

Nurullah Taş

Chapter Highlights

- Explores the integration of generative artificial intelligence with gamification to support adaptive and interactive learning environments.
- Examines how AI-driven personalization enhances learner engagement, motivation, and learning outcomes.
- Synthesizes current empirical and conceptual research on generative AI–based gamification across educational levels.
- Discusses teacher and learner perspectives on AI-supported interactive learning systems.
- Identifies ethical, pedagogical, and technical challenges associated with generative AI–driven gamified learning.
- Outlines future research directions for theory-informed and human-centered AI-enhanced gamification.

Introduction

Generative artificial intelligence (GenAI) has emerged as a transformative technology in education by enabling learning environments that are adaptive, personalized, and interactive. Unlike traditional educational technologies that rely on predefined content and static feedback, generative AI can dynamically produce learning tasks, feedback, and interactive elements in response to learners' needs and behaviors.

Gamification and interactive learning approaches aim to enhance learner engagement and motivation through active participation and game-inspired design elements. However, conventional gamified systems are often limited in their ability to adapt to individual learners. The integration of generative AI addresses this limitation by supporting real-time personalization, adaptive challenges, and context-aware feedback.

This chapter examines the role of generative artificial intelligence in gamification and interactive learning. It outlines the conceptual foundations of this integration, discusses its potential impact on learning outcomes and learner experiences, and highlights key pedagogical and ethical considerations for future educational applications.

Digital transformation in education and generative AI

Over the past decade, digital transformation has shifted from a peripheral innovation project to a core strategic priority for education systems worldwide. In higher education, digital transformation refers not only to the adoption of digital tools, but to a broad reconfiguration of processes, organizational models, and learning experiences enabled by emerging Technologies (Benavides et al., 2020; Fernández et al., 2023). Universities and schools are rethinking how they manage information, design curricula, support learners, and interact with external stakeholders in order to remain competitive and to prepare students for increasingly digital societies and labor markets (Hashim et al., 2021; Surjawan et al., 2025).

This transformation accelerated sharply during the COVID-19 pandemic, which exposed gaps in schools' digital capacity and widened existing inequalities where infrastructure, skills, and support were insufficient (Iivari et al., 2020; Timotheou et al., 2022). Reviews of digital technology in education show that its impact extends well beyond test scores, reshaping teacher roles, professional development, school organization, and policy agendas (Z. Wang et al., 2024). Nonetheless, empirical studies indicate that, in many contexts, digital media are still used mainly for basic, assimilative tasks rather than more transformative, student-centered practices (Bond et al., 2018).

Within this broader digital transformation, generative artificial intelligence (GenAI) has emerged as a particularly disruptive force. Generative AI systems—such as large language models and multimodal generators—can create new text, images, code, and other content, enabling applications in assessment, personalized learning support, simulation, and intelligent tutoring (Bahroun et al., 2023; Ruiz-Rojas et al., 2023). Scoping and commentary work highlights GenAI's potential to support self-directed learning, writing assistance, adaptive feedback, and teacher planning, while also surfacing concerns around accuracy, "hallucinated" information, academic integrity, bias, and over-reliance on automated tools (Mao et al., 2023; Preiksaitis & Rose, 2023).

Recent empirical and conceptual studies suggest that, when thoughtfully integrated, generative AI can enhance innovation capability, digital literacy, and self-regulated learning by supporting active engagement, immediate feedback, and personalized scaffolding (Kong & Yang, 2024). At the same time, systematic and multivocal reviews of digital transformation in higher education show that many institutions are still at an early stage of digital maturity, implementing isolated initiatives without coherent strategies, governance, or ethical frameworks for AI (Benavides et al., 2020). This tension situates GenAI as both a catalyst and a test case for digital transformation in education: its rapid diffusion forces institutions to confront questions about pedagogy, assessment, data governance, academic integrity, and human–AI collaboration.

Against this backdrop, examining digital transformation in education through the lens of generative AI is timely and necessary. It allows exploration of how AI-driven tools may move educational systems from digitization toward deeper, systemic change, while clarifying the competencies, policies, and design principles required to leverage GenAI responsibly in service of equitable, human-centered learning (Bahroun et al., 2023).

The convergence of generative AI, gamification, and interactive learning

The rapid expansion of generative artificial intelligence (GenAI), together with advances in gamification and interactive learning technologies, is reshaping how educational experiences are designed, delivered, and personalized. GenAI systems such as large language models can generate text, images, code, simulations, and feedback on demand, supporting personalized tutoring, content creation, and adaptive assessment at scale (Mittal et al., 2024; Yan et al., 2024). At the same time, gamification and game-based learning have matured as approaches that leverage points, challenges, narratives, and feedback to increase motivation, engagement, and persistence in both online and blended learning environments (Bennani et al., 2021; Kassenkhan et al., 2025). Interactive learning platforms that embed simulations, branching scenarios, and real-time feedback further transform learners from passive recipients into active participants in dynamic digital environments (Aashmi & Reddy, 2025).

Emerging research suggests that the convergence of these three strands—GenAI, gamification, and interactivity—can enable deeply personalized, data-rich, and motivating learning experiences. GenAI can act as an interactive scaffold within educational games, providing instant, context-sensitive feedback, hints, and dialogue that support flow and reduce anxiety during complex tasks (Chien et al., 2024). Integrating GenAI into gamified systems also opens possibilities for adaptive narratives, dynamic quest generation, and tailored difficulty curves that are responsive to learner profiles, needs, and motivations (Abbes et al., 2024; Moon et al., 2024). Studies on AI-enhanced gamification show that adaptive learning paths and conversational agents can significantly improve both learning outcomes and nonlinear, dynamic motivation, particularly in language and STEM education (Liu, 2024).

These developments are supported by broader trends in AI-powered interactive learning platforms and educational analytics. AI-driven environments increasingly combine bilingual or multimodal content, interactive 2D/3D simulations, and gamified elements with real-time data analytics to personalize learning trajectories and support

diverse learners (Mullah & Jayachandran, 2025). GenAI's features of autonomy, interactivity, and usability are associated with higher engagement and skill development, especially when systems provide learners with meaningful choices and personalized support (Nguyen et al., 2025). Conceptual and empirical work further indicates that GenAI can streamline instructional design for gamification, helping educators prototype complex game mechanics, storylines, and assessments while lowering the expertise and time barriers to high-quality gameful design (Rosunally, 2024).

At the same time, this convergence raises critical questions about ethics, equity, and pedagogy. Reviews highlight challenges related to bias, transparency, academic integrity, and the risk of over-automation in AI-driven educational games and platforms (Mittal et al., 2024). Scholars emphasize the need for robust frameworks for adaptive gamification, including learner-aware design, explainable adaptation mechanisms, and alignment with motivational and learning theories (Abbes et al., 2024; Bennani et al., 2021). As interest in generative AI–driven gamification grows across disciplines, calls are emerging for systematic research on human–AI co-creation, hybrid classrooms, and the long-term effects of highly personalized gameful environments on cognition, motivation, and critical thinking (Moon et al., 2024).

Within this evolving landscape, the convergence of generative AI, gamification, and interactive learning represents a pivotal frontier for educational innovation. Understanding how these technologies can be orchestrated to create engaging, equitable, and pedagogically sound learning experiences—while managing their risks—has become a central agenda for researchers, designers, and policymakers in technology-enhanced learning.

Purpose and scope of the chapter

The purpose of this chapter is to examine how generative artificial intelligence can be integrated with gamification and interactive learning to enhance learner engagement, motivation, and learning outcomes. Specifically, the chapter aims to clarify the conceptual foundations of generative AI–driven gamification, explore its pedagogical potential, and identify the mechanisms through which adaptive and personalized learning experiences can be designed.

In terms of scope, the chapter provides a focused discussion of generative AI–supported gamification mechanics, adaptive interactive learning environments, and their implications for teaching and learning across different educational contexts. Empirical findings related to academic achievement, motivation, and self-regulated learning are reviewed, alongside teacher and learner perspectives. The chapter also addresses ethical, pedagogical, and technical challenges associated with the use of generative AI in gamified learning environments and concludes by outlining future research directions and practical considerations for educational practice.

Generative Artificial Intelligence

Generative artificial intelligence (GenAI) refers to a subset of artificial intelligence techniques capable of producing seemingly new, meaningful content—such as text, images, audio, code, or video—by learning patterns

from large collections of training data and then sampling from these learned distributions (Feuerriegel et al., 2023; Ramamoorthy, 2025; Sengar et al., 2024). Unlike traditional, predominantly discriminative AI systems that focus on classification or prediction, generative models aim to create data that resemble human-produced artifacts, enabling more open-ended, creative, and interactive applications across domains ((Banh & Strobel, 2023; Uddin et al., 2025). This shift has been enabled by deep generative architectures such as generative adversarial networks (GANs), variational autoencoders (VAEs), transformer-based large language models (LLMs), and diffusion models (Çelik & Eltawil, 2024; Sengar et al., 2024; Uddin et al., 2025).

In a short period, GenAI has moved from research laboratories into widespread public and organizational use, with systems like GPT-4, DALL·E, and Copilot transforming content creation, decision support, and human–computer interaction (Ooi et al., 2023). Systematic and tutorial reviews document how GenAI now underpins applications in natural language generation, image translation, creative industries, healthcare, wireless communications, and assistive technologies, among many others (Çelik & Eltawil, 2024). In business and management, GenAI is viewed as a driver of business model innovation and organizational transformation, enabling novel value propositions, process automation, and new forms of digital service delivery (Kanbach et al., 2023; Storey et al., 2025). Across education and learning analytics, GenAI supports automated feedback, content generation, and synthetic data creation, while simultaneously challenging existing practices in assessment and academic integrity (Misiejuk et al., 2025; Preiksaitis & Rose, 2023).

At the same time, the rapid diffusion and distinctive capabilities of GenAI raise substantial ethical, social, and regulatory concerns. Interdisciplinary reviews highlight issues related to privacy, data protection, deepfakes, misinformation, bias, intellectual property, environmental impact, and the potential exacerbation of existing social inequalities (Al-Kfairy et al., 2024; Stahl & Eke, 2024; Zohny et al., 2023). In high-stakes domains such as healthcare, assistive technologies, and education, concerns about explainability, trustworthiness, accuracy, and over-dependence are particularly salient (Chataut et al., 2025). Scholars therefore call for responsible AI frameworks, robust evaluation methods, and multidisciplinary governance approaches to ensure that generative systems are aligned with human rights, fairness, and broader societal values (Al-Kfairy et al., 2024; Ooi et al., 2023; Ramamoorthy, 2025).

Given its technical foundations, broad application spectrum, and significant societal implications, generative AI has become a focal topic for research across computer science, information systems, ethics, and sector-specific fields. Clarifying what GenAI is, how it differs from earlier AI paradigms, and how its affordances and risks play out in real-world contexts is essential for harnessing its transformative potential while mitigating its harms (Banh & Strobel, 2023; Feuerriegel et al., 2023; Ooi et al., 2023).

Gamification in Education

Gamification in education broadly refers to the use of game design elements and gameful experiences in non-game learning contexts to stimulate motivation, engagement, and persistence(Deterding et al., 2011; Manzano-León et al., 2021; Meng et al., 2024) . Typical elements include points, badges, leaderboards, levels, progress bars, challenges, and narratives, which are layered onto existing activities rather than replacing curricular content

with full games (Khaldi et al., 2023). This approach has gained prominence alongside the growth of digital and online learning, where low completion and high dropout rates are frequently linked to insufficient student motivation and interaction (Antonaci et al., 2019; Khaldi et al., 2023).

Systematic reviews and meta-analyses generally indicate that well-designed gamified learning can yield small-to-moderate positive effects on cognitive, motivational, and behavioral outcomes. A meta-analysis reported significant positive effects of gamification on learning performance, motivation, and behavioral engagement, suggesting that game elements can be effective instructional supports (Sailer & Homner, 2019). Likewise, reviews of online and higher education environments show that gamification can enhance engagement, participation, and course satisfaction, and may improve achievement and retention in some contexts (Antonaci et al., 2019; James et al., 2024; Manzano-León et al., 2021). Studies in vocational and medical education also highlight gains in motivation, engagement, and practical competence when gamified systems and simulations are integrated into training and blended e-learning (Dahalan et al., 2023; Jayalath & Esichaikul, 2020).

Despite this promise, the evidence base remains heterogeneous and context dependent. Critical reviews emphasize that much empirical work suffers from short intervention durations, small samples, and limited theoretical grounding, making it difficult to generalize long-term benefits (Dichev & Dicheva, 2017; Zainuddin et al., 2020). The effectiveness of specific elements such as points and badges appears to vary with learner characteristics, domain, and instructional design, and there is ongoing debate about overreliance on extrinsic rewards and the risk of undermining intrinsic motivation (Meng et al., 2024; Ukgoda, 2025). Recent scholarship therefore calls for adaptive and theory-driven gamification, aligning mechanics with motivational theories such as self-determination theory and tailoring experiences to individual needs, values, and learning contexts (Bennani et al., 2021; Khaldi et al., 2023).

Within this evolving landscape, gamification is increasingly viewed not as a universal solution but as a powerful, design-sensitive strategy that can enrich educational environments when carefully integrated with sound pedagogy, clear learning objectives, and ongoing evaluation (Sailer & Sailer, 2020; Antonaci et al., 2019) (Antonaci et al., 2019; Sailer & Sailer, 2020).

Interactive Learning Approaches

Interactive learning approaches place learners in active, dialogic, and participatory roles, emphasizing collaboration, problem solving, and continuous feedback rather than one-way transmission of information (Prykhodkina et al., 2025; Wekerle et al., 2024). Rooted in constructivist views of learning, these approaches assume that knowledge is co-constructed through social interaction, reflection, and engagement with authentic tasks. Typical strategies include collaborative projects, problem-based learning, peer assessment, project-based online learning, game-based learning, and technology-supported interaction such as simulations, clickers, and interactive digital platforms (Aparicio-Gómez et al., 2024; Gan et al., 2015; Mora et al., 2020).

Chapter 3: Generative Artificial Intelligence, Gamification, and Interactive Learning

The growing integration of digital and emerging technologies has broadened the scope and potential of interactive learning. Technology-enhanced environments now incorporate interactive simulations, audience response systems, adaptive platforms, and collaborative social learning tools that support discussion, group work, inquiry, and peer feedback (Gan et al., 2015; Wekerle et al., 2024; Yaseen et al., 2025). For example, PhET simulations in physics classes enable students to test hypotheses and visualize complex phenomena, leading to higher motivation and achievement compared with conventional instruction (Banda & Nzabahimana, 2022). Similarly, design-based research on learning technology tools in higher education shows that interactive response systems and structured peer assessment can promote participation, deeper processing, and constructive feedback among students (Y.-H. Wang, 2020).

Empirical evidence across school and university settings links interactive learning approaches to enhanced engagement, motivation, and academic performance. Studies in elementary and secondary schools indicate that collaborative projects, gamification, and technology-enhanced activities foster more stimulating classroom environments, increasing motivation and improving learning outcomes (Banda & Nzabahimana, 2022; Prameswari et al., 2025). In higher education, interactive digital media, collaborative platforms, and peer-review models are associated with greater content assimilation, development of scientific and professional competencies, and higher-quality work than students typically achieve individually (Gan et al., 2015; Mora et al., 2020; Prykhodkina et al., 2025). Systematic reviews of blended and innovative teaching further highlight interactive lessons, project-based learning, flipped classrooms, and peer feedback as key techniques that positively affect student motivation and academic achievement (Daniel et al., 2024; Martinez & Gomez, 2025).

At the same time, research underscores that the effectiveness of interactive approaches depends on careful pedagogical design, alignment with learning objectives, and attention to contextual factors such as digital literacy, institutional support, and time demands on instructors (Prykhodkina et al., 2025; Yaseen et al., 2025; Wekerle et al., 2024) (Prykhodkina et al., 2025; Wekerle et al., 2024; Yaseen et al., 2025) . These findings position interactive learning not as a single method, but as a family of design-sensitive strategies that, when thoughtfully implemented, can support deeper understanding, critical thinking, and the development of 21st-century skills.

Generative AI-Driven Gamification Mechanics

Generative artificial intelligence (GenAI) is reshaping how game elements are conceived, delivered, and adapted in educational environments. Moving beyond static points, badges, and leaderboards, generative AI-driven gamification mechanics leverage models such as large language models and generative adversarial networks to create dynamic narratives, adaptive challenges, and real-time feedback tailored to individual learners (Abbes et al., 2024; Mittal et al., 2024). In education, this convergence aims to couple the motivational power of gamification with GenAI's capacity for on-the-fly content generation and personalization.

Recent work outlines frameworks in which GenAI acts as a *design and runtime engine* for gamified learning. For educators, AI assistants can automatically propose game loops, missions, reward structures, and narrative themes from curricular inputs, lowering expertise and time barriers traditionally associated with gamification design (Rosunally, 2024). Tools such as custom GPT-based assistants and AI-assisted gamification frameworks show

that GenAI can generate context-appropriate rules, storylines, and progression systems across diverse disciplines while preserving pedagogical intent (Rosunally, 2024). At runtime, GenAI-enabled systems can also scaffold learner interactions through instant, dialogic feedback and hints embedded in role-playing or scenario-based games, sustaining flow and reducing anxiety (Chien et al., 2024).

At the level of game mechanics, GenAI facilitates adaptive and personalized challenges, dynamic difficulty adjustment, and intelligent feedback loops. AI-enhanced gamification can construct individualized learning pathways, automatically modulate task complexity, and generate fine-grained formative feedback and assessments, which together have been linked to higher engagement, motivation, and academic performance (Alanzi & Taloba, 2025; Dahri et al., 2025; Jiali, 2025). In language and computing education, for example, GPT-based systems have been used to create gamified programming exercises, rich practice scenarios, and adaptive assessments that respond to learner inputs in real time (Alanzi & Taloba, 2025; Pang & Wei, 2025; Salmanova, 2025).

Scholars also highlight important design and ethical challenges. GenAI-driven mechanics introduce new risks, including cognitive overload from incessantly generated stimuli, over-reliance on AI rather than human interaction, and potential bias or opacity in adaptive reward and progression systems (Mittal et al., 2024; Moon et al., 2024; Salmanova, 2025). Effective use therefore requires theory-informed alignment with motivational frameworks, careful curation of AI outputs, and attention to issues of privacy, transparency, and (Abbes et al., 2024; Moon et al., 2024). As research on GenAI in educational game design and AI-linked gamification continues to grow, generative AI-driven gamification mechanics are emerging as a promising but design-sensitive approach to creating adaptive, immersive, and scalable learning experiences (Kassenkhan et al., 2025; Moon et al., 2024).

Adaptive Interactive Learning Environments Enabled by Generative AI

Generative artificial intelligence (GenAI) is enabling a new class of adaptive interactive learning environments that respond to learner needs in real time. Unlike earlier rule-based adaptive systems, GenAI can dynamically generate explanations, examples, activities, and feedback while simultaneously modeling learner behavior and preferences, supporting highly personalized pathways at scale (Guettala et al., 2024; Mittal et al., 2024). In these environments, large language models and other generative architectures act as conversational tutors, content generators, and recommendation engines that adjust instruction based on performance data, engagement patterns, and learner input (Maity & Deroy, 2024).

Recent work documents how GenAI-driven platforms adapt multiple dimensions of the learning experience. At the content level, GenAI can produce diverse, multimodal resources—texts, images, videos, and interactive activities—aligned with learning outcomes and tailored to individual interests or reading levels (Pesovski et al., 2024). At the interaction level, GenAI-powered tutors and assistants support dialogic questioning, on-demand clarification, and formative assessment, thereby creating responsive, learner-centered environments that can adjust difficulty, pacing, and scaffolding on the fly (Anderson et al., 2025; Maity & Deroy, 2024). Human-in-the-loop designs further show how student and teacher feedback can be incorporated into

retrieval-augmented generation pipelines to iteratively refine explanations and examples for different learners in STEM domains (Tarun et al., 2025).

Empirical and conceptual studies suggest that such adaptive interactive environments can enhance engagement, efficiency, and inclusivity. Case analyses of GenAI-enabled adaptive systems report increased student engagement, improved test scores, and faster skill acquisition when AI-driven personalization is combined with traditional pedagogy (Cosentino et al., 2025; Guettala et al., 2024). Experiments in embodied and game-based settings indicate that GenAI-generated feedback can maintain or improve learning outcomes while reducing cognitive load and supporting flow, especially when interactive scaffolding is tightly integrated into the task (Chien et al., 2024; Cosentino et al., 2025). For learners with disabilities and diverse needs, adaptive systems that combine multimodal generative content, real-time monitoring, and reinforcement-learning-based feedback have been shown to improve participation, retention, and learning outcomes by tailoring supports to cognitive, sensory, and behavioral profiles (Barbu et al., 2025; Farhah et al., 2025).

At the same time, scholars emphasize that the design of GenAI-enabled adaptive environments must remain human-centered and ethically grounded. Key concerns include safeguarding privacy, mitigating algorithmic bias, ensuring pedagogical soundness, and preventing over-reliance on AI at the expense of human agency and social connection (Kong & Yang, 2024; Mittal et al., 2024). Frameworks that integrate GenAI into established models such as the Community of Inquiry and self-regulated learning highlight teachers' evolving roles as facilitators, curators, and co-designers of AI-supported experiences rather than as mere overseers of automated systems (Anderson et al., 2025; Kong & Yang, 2024). Together, these developments position adaptive interactive learning environments enabled by GenAI as a promising yet design-sensitive frontier for creating more responsive, inclusive, and scalable education.

Effects of Generative AI-Based Gamification on Learning Outcomes

The convergence of generative artificial intelligence (AI) and gamification is reshaping how learning outcomes are achieved and measured in contemporary education. Gamification traditionally employs elements such as points, leaderboards, challenges, and narratives to increase motivation and engagement; when combined with AI—especially generative and adaptive models—these elements can be personalized, continually adjusted, and informed by rich learner data, creating more responsive learning environments (Jiali, 2025; Kassenkhan et al., 2025). AI-driven gamification systems are increasingly able to generate context-sensitive tasks, tailored feedback, and adaptive difficulty, transforming static game mechanics into dynamic learning experiences that directly target academic achievement, skills development, and knowledge retention (Bachiri et al., 2023).

Empirical research across disciplines shows consistently positive, though nuanced, effects of AI-based gamification on learning outcomes. Structural equation modeling and experimental studies report that AI-supported gamification significantly improves student achievement and performance, often mediated by increased engagement and motivation (Dahri et al., 2025; Singh, 2025). In language education, AI-enhanced gamified environments have been associated with higher post-test scores, superior language proficiency gains, and improved retention compared to traditional instruction or non-AI gamified approaches (Duisenova &

Zhorabekova, 2023; Safdar et al., 2025). AI-assisted game-based learning with conversational agents such as ChatGPT has also been shown to elevate science learning outcomes, perceived competence, and effective learning behaviors while simultaneously reducing cognitive load (Chen & Chang, 2024). Systematic and bibliometric reviews converge on similar conclusions, highlighting that AI-driven gamification supports better academic performance by enabling personalized learning pathways, timely feedback, and challenge levels calibrated to learners' abilities (Cruz et al., 2025; Jiali, 2025; Marengo et al., 2025).

At the same time, the literature emphasizes that the impact of generative AI-based gamification depends on careful design and contextual factors. Not all implementations yield clear gains in higher-order outcomes or long-term retention; some studies find strong effects on engagement and interaction metrics without a direct, immediate translation into durable knowledge gains or reduced dropout (Gasparin et al., 2025). Challenges include over-reliance on technology, unequal access to AI-powered platforms, and increased stress or cognitive demands when systems are poorly aligned with pedagogy (Safdar et al., 2025). Teachers' perspectives further underscore implementation barriers such as professional development needs, technical issues, and curriculum alignment, even as they overwhelmingly perceive short-term improvements in motivation, participation, and learning outcomes in AI-driven gamified classrooms (Alenezi, 2023).

Overall, emerging evidence suggests that generative AI-based gamification can meaningfully enhance learning outcomes—ranging from test performance and language proficiency to problem-solving and AI literacy—when it is grounded in sound instructional design, aligned with motivational theory, and supported by adequate teacher training and infrastructure (Chen & Chang, 2024). Ongoing research calls for longitudinal and comparative studies to clarify sustained effects, optimize generative AI's role in game mechanics, and address ethical and equity concerns surrounding data use and access (Alenezi, 2023; Marengo et al., 2025).

Teacher and Learner Perspectives

Understanding how teachers and learners perceive educational technologies is central to explaining why some innovations become embedded in practice while others remain peripheral. Research consistently shows that educators' beliefs about usefulness, ease of use, and pedagogical fit strongly shape their willingness to adopt tools such as learning management systems, learning analytics dashboards, and artificial intelligence (AI)–enhanced applications (Granić, 2022; Shibani et al., 2020; Zakaria et al., 2021). Systematic reviews of technology adoption models highlight teacher-related factors—self-efficacy, perceived enjoyment, anxiety, and facilitating conditions—as key predictors of actual use, suggesting that teachers function as critical gatekeepers of technology-rich learning environments (Backfisch et al., 2021; Granić, 2022). At the same time, learners' experiences of motivation, engagement, and cognitive load determine whether these environments translate into meaningful learning outcomes and sustained use (Öberg et al., 2024; Panigrahi et al., 2018).

Recent work on AI and smart digital technologies illustrates the complexity of teacher and learner perspectives. Teachers commonly recognize that AI-enabled tools can save time, support differentiated instruction, and enrich classroom activities, yet they also express concerns about technical challenges, job displacement, ethical risks,

and the erosion of "human touch" in teaching (Alwaqdani, 2024; Filiz et al., 2025). Studies of AI-assisted content creation and feedback systems show that perceived usefulness and ease of use strongly predict teachers' intentions to integrate such tools, while insufficient infrastructure and training remain major barriers, especially in less-resourced contexts (Malakul, 2025; Zakaria et al., 2021). From learners' perspectives, AI-integrated applications and gamified platforms can simultaneously enhance engagement, personalized feedback, and creativity, and yet also induce performance anxiety, emotional disengagement, and worries about over-reliance on automated support (Panigrahi et al., 2018).

A growing body of multi-stakeholder research underscores that teacher and learner perspectives are not always aligned. While teachers may prioritize issues of control, assessment integrity, and curricular alignment, students tend to foreground immediacy of support, usability, and perceived fairness or justice in AI-driven systems (Ahmed, 2025; Karran et al., 2024). Comparative and cross-cultural studies further show that attitudes toward gamification, AI-based assessment, and data-driven personalization vary by educational system and sociocultural context, with implications for global technology deployment (Chawla, 2023; Muthulakshmi & Arjumand, 2024). Taken together, this literature suggests that any robust account of technology-mediated learning must integrate both teacher and learner perspectives, attending to their convergences and tensions in order to design ethically responsible, pedagogically sound, and context-sensitive educational innovations.

Applications Across Educational Levels

Artificial intelligence (AI) and AI-enhanced gamification are being adopted from early childhood through higher education, but their roles and design priorities differ markedly by educational level. In K–12 settings, AI is used both as a content (AI literacy) and as a tool to support learning, with an emphasis on age-appropriate interfaces, play- and game-based approaches, and the development of computational thinking and foundational skills (Zafari et al., 2022). Scoping and systematic reviews show that intelligent agents, visual machine-learning tools, and educational robots help younger learners experiment with AI concepts, while block-based programming and introductory coding environments support algorithmic thinking in upper primary and secondary school (Yim & Su, 2024; Zafari et al., 2022). In these contexts, gamification and AI are frequently embedded in project-based and game-based activities aiming to foster cognitive, affective, and behavioral outcomes rather than high-stakes assessment (Kurnaz & Koçtürk, 2025; Yim & Su, 2024).

At the secondary level, AI-supported applications become more targeted toward academic performance, motivation, and at-risk student identification. Meta-analytic evidence indicates that gamification has its strongest motivational impact among secondary students, with progressively smaller effects in high school and primary grades, suggesting developmental differences in how learners respond to game (Kurnaz & Koçtürk, 2025). AI systems in school contexts are increasingly used for predictive modeling, adaptive feedback, and learning analytics dashboards that help teachers monitor engagement and intervene early to prevent dropout, although adoption in primary and secondary education remains more cautious than in higher education (Demartini et al., 2024; Zafari et al., 2022).

In higher education, AI applications expand substantially, supporting learning, teaching, and institutional administration. Systematic reviews and regional analyses highlight widespread use of machine learning and natural language processing for predictive analytics, intelligent tutoring, automated feedback on writing, and adaptive learning pathways (Amoako et al., 2024; Msambwa et al., 2025; Salas-Pilco & Yang, 2022). AI-driven gamification and adaptive learning paths are leveraged to personalize instruction, increase engagement, and improve academic performance in undergraduate courses, including language learning and STEM disciplines (Dahri et al., 2025; Jiali, 2025). At this level, AI is also integrated into research training, academic integrity systems, and institutional decision-making, illustrating a broader organizational embedding of AI beyond the classroom (Escotet, 2023; Salas-Pilco & Yang, 2022).

Taken together, the literature suggests a continuum of applications: playful, exploratory AI tools in early schooling; motivational and diagnostic systems in secondary education; and deeply integrated, data-intensive, and governance-oriented AI infrastructures in higher education (Demartini et al., 2024; Msambwa et al., 2025; Yim & Su, 2024). These differences underscore the need for level-specific design, teacher preparation, and policy frameworks to ensure that AI and AI-enhanced gamification advance equitable and meaningful learning across the educational lifespan.

Ethical, Pedagogical, and Technical Challenges

The rapid integration of artificial intelligence (AI), generative AI, and AI-driven gamification into education brings not only new opportunities but also a layered set of ethical, pedagogical, and technical challenges that shape whether these technologies ultimately benefit learners. Ethical concerns centre on data privacy, surveillance, algorithmic bias, autonomy, and equity. AI systems require extensive collection and processing of student data, raising risks of breaches, opaque profiling, and institutional misuse when safeguards and regulatory oversight are weak (Dhiman et al., 2025; García-López & Trujillo-Liñán, 2025). Studies of AI in schools and higher education highlight worries about continuous monitoring, erosion of anonymity, and the reproduction of existing social and educational inequalities through biased training data and decision-making models (Farooqi et al., 2024; Regan & Jesse, 2018; Shukla & Merikapudi, 2025). Generative AI adds further concerns around academic plagiarism, loss of cognitive autonomy, misinformation, and unclear accountability for AI-generated content (Adel et al., 2024; Ali et al., 2025; García-López & Trujillo-Liñán, 2025).

Pedagogically, AI tools can support personalization and engagement, yet they also disrupt established roles and practices. Reviews and empirical studies show tensions between automation and the preservation of meaningful teacher–student interaction, with fears that over-reliance on AI may weaken critical thinking, reduce human feedback, and reconfigure assessment in ways that prioritize efficiency over deep learning (Abimbola et al., 2024; Bing & Leong, 2025; Safdar et al., 2025). Educators report uncertainty and resistance when AI challenges traditional assessment norms or introduces opaque recommendation and grading systems, underscoring the need for professional development that addresses both ethics and pedagogy (Mouta et al., 2024; Pandey, 2025). There is also a risk that personalized and gamified pathways function as subtle “tracking” mechanisms, sorting students into differentiated trajectories with limited transparency or opportunities for contestation (Regan & Jesse, 2018).

Technically, many institutions struggle with the infrastructure, expertise, and governance required for reliable and equitable AI deployment. Systematic reviews categorize obstacles such as limited computational resources, integration difficulties with legacy systems, lack of explainability, and dependence on proprietary platforms that constrain local control (Abbes et al., 2024; Ali et al., 2025; Farooqi et al., 2024). These technical constraints intersect with the digital divide: unequal access to devices, connectivity, and localized tools can exacerbate educational disparities, particularly in under-resourced contexts (Abimbola et al., 2024; Santos et al., 2025). Addressing ethical, pedagogical, and technical challenges in a coherent way therefore requires ethics-by-design approaches, robust governance frameworks, and sustained teacher training to ensure that AI-enhanced education remains transparent, accountable, and pedagogically meaningful (Bing & Leong, 2025; García-López & Trujillo-Liñán, 2025).

Future Trends and Research Directions

Future developments in artificial intelligence (AI), generative AI, and gamified learning in education are expected to move from isolated tools toward integrated, human-centered ecosystems that combine technical innovation with ethical governance and pedagogical redesign. Reviews and expert Delphi studies emphasize that forthcoming work must prioritize trustworthy, transparent, and fair AI systems, with privacy, ethical use of big data, and equity repeatedly identified as high-impact trends and challenges for the next several years (Bulathwela et al., 2024; Ifenthaler et al., 2024; Kamalov et al., 2023). This requires not only technical advances in explainable and bias-aware algorithms, but also robust policy frameworks and institutional guidelines for responsible, inclusive AI at scale (Ifenthaler et al., 2024).

On the pedagogical side, future research is expected to shift from proof-of-concept deployments toward rigorous, longitudinal, and comparative studies that measure learning, motivation, equity, and teacher workload across diverse contexts. Scholars call for empirical evaluations comparing AI-enhanced and traditional instruction, investigating long-term impacts of generative AI on academic integrity, self-regulated learning, and higher-order skills, and examining teacher roles in AI-supported classrooms (Adel et al., 2024; Celik et al., 2022; Kamalov et al., 2023). There is also growing interest in how AI-driven personalization, adaptive gamification, and smart classrooms can be co-designed with teachers and learners, rather than imposed as top-down solutions (Abbes et al., 2024; Bennani et al., 2021; Dimitriadou & Lanitis, 2023).

Technically, several converging trajectories are highlighted: integration of AI with emerging technologies such as virtual/augmented reality, Internet of Things, and learning analytics dashboards; development of dynamic adaptation engines that fuse generative AI with gamification; and exploration of new algorithmic paradigms like deep learning, swarm intelligence, and neuroscience-informed models (Bennani et al., 2021). At the same time, future work must address infrastructural limitations and the digital divide to avoid exacerbating educational inequalities, especially in rural and under-resourced settings (Bulathwela et al., 2024; Castro et al., 2025). Overall, the emerging agenda points toward interdisciplinary, equity-driven research that treats AI not as a standalone solution, but as a component of broader efforts to transform teaching, assessment, and educational governance.

Conclusion

The convergence of generative artificial intelligence, gamification, and interactive learning represents a significant shift in the design and delivery of educational experiences. By enabling dynamic content generation, adaptive challenges, and personalized feedback, generative AI extends traditional gamification beyond static mechanics toward responsive, learner-centered learning environments. Evidence reviewed in this chapter suggests that such systems can positively influence motivation, engagement, and academic performance when grounded in sound pedagogical principles.

At the same time, the effective use of generative AI–driven gamification depends on careful instructional design, teacher involvement, and ethical governance. Issues related to data privacy, algorithmic bias, transparency, and over-reliance on automation require sustained attention to ensure that AI-enhanced learning remains equitable and pedagogically meaningful. Teachers' roles as designers and facilitators remain central, while learners' experiences and perceptions shape the educational value of these systems.

Overall, generative AI–based gamification should be viewed not as a standalone solution, but as part of a broader transformation toward adaptive, interactive, and human-centered education. Future research should focus on longitudinal impacts, theory-driven design frameworks, and context-sensitive implementations to fully realize the potential of generative AI in gamified and interactive learning environments.

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Chapter 4- Artificial Intelligence Applications in Cyber Security

Hasan Küçükoğlu

Chapter Highlights

- AI, when integrated into cyber security strategies, offers dynamic and proactive security measures that enable faster and more accurate detection and analysis of threats.
- AI-enhanced risk assessment and reaction systems quickly identify threats, prioritize defensive measures, and develop effective responses to cyberattacks.
- AI-based defense approaches detect cyber threats at earlier stages, classify them accurately, and strengthen defense strategies with an effective security architecture.
- AI-powered cyber security applications create a multi-layered security ecosystem, offering proactive and adaptable defense solutions for both corporate and individual users.
- The future of AI-based cyber security systems will provide faster and more effective defense against cyber threats with more flexible, autonomous, and learning-based solutions.

Introduction

Artificial intelligence (AI) and cyber security are two critical areas that are closely intertwined in the modern technology landscape. Particularly in recent years, the rapid advancement of digitalization has led to an increase in the number of connected devices and accelerated big data flows, resulting in more complex and widespread cyber threats. In this context, the integration of AI techniques into cyber security strategies is seen as an important component for both preventing attacks and optimizing security processes. AI has great potential in identifying, analyzing, and managing risks in cyber security, while also offering a more dynamic, adaptable, and proactive approach to cyber security (Zhang, 2024).

Machine learning (ML) and deep learning (DL), which have developed concurrently with artificial intelligence, hold a crucial place in cyber security applications as subfields of AI. Machine learning enables computers to learn from data and make predictions based on past experiences, and is used to detect anomalous activity. Deep learning, on the other hand, is a method that offers significant advantages, particularly in recognizing complex patterns, classifying attacks according to attack type, and predicting potential threats. By combining these two techniques, artificial intelligence enables cyber security systems to learn automatically and continuously, making attack detection and response processes more effective (Ofusori et al., 2024).

Within the framework of cyber security, the process of determining and evaluating the attack profile and the process of implementing appropriate solutions should be considered as a whole. From this perspective, real-time attack detection stands out as a critical area requiring immediate intervention by machines, as one of the cornerstones of cyber security. In this process, the use of machine learning algorithms helps to quickly detect cyber threats, while risk assessment and response systems are also seen as an integral part of cyber security processes. These systems help prioritize defensive measures by measuring the potential impact of attacks. AI-powered dynamic systems enhance the effectiveness of security strategies by providing systematic and timely responses based on the nature of any threat (Folorunso et al., 2024).

One of the steps implemented in this context, defense approaches and security architectures, provide an important framework for how AI should be integrated into cyber security. AI-powered security architectures enable attacks to be detected at earlier stages, threats to be classified more accurately, and the impact of attacks to be minimized. At the same time, the use of AI technologies in different areas such as network security, authentication, data protection, and encryption helps develop defense mechanisms. This makes cyber security infrastructures more flexible, compliant, and resilient (Michael et al., 2023).

When the relationship between AI and cyber security is evaluated in general, AI-powered cyber security applications operate across multiple layers, from basic security measures to the broader ecosystem level. At every layer of the cyber security ecosystem, various AI applications cover a wide range, from early detection of threats to rapid neutralization of attacks. In these applications, AI facilitates information sharing and coordination between security measures at each layer, while also providing proactive defense against attackers' strategies, making the security ecosystem more resilient and adaptable to attacks (Taherdoost, 2025).

Conceptual Framework of Cyber Security and AI

AI is defined as a machine-based system that can influence its environment by generating output for a specific set of purposes, such as predictions, recommendations, or decisions. The basic working mechanism of this system is defined as perceiving real or virtual environments with machine- or human-based data and inputs; analyzing these perceptions automatically or manually and converting them into models; and creating options for results using model inference (Xu et al., 2025).

From this perspective, AI systems are designed to operate at different levels of autonomy for specific purposes. AI is particularly effective in detecting, analyzing, and preventing cyber security threats, especially in closely related subfields. As the autonomy level of AI increases, countermeasures against attacks can be implemented more quickly and security protocols become more dynamic. Furthermore, thanks to its continuous learning and adaptation capabilities, AI performs the analysis and management of evolving threats more effectively. Therefore, AI-based systems form the basis of a more proactive and sustainable cyber security approach by automating security processes (Malatji & Tolah, 2025).

At this point, the relationship between AI and cyber security takes shape in three dimensions (EU, 2024):

- **Standardization Use of AI in Cyber Security:** This dimension involves the creation of standards for the safe and effective use of AI applications in the field of cyber security. AI-supported security systems that are compatible and can work together in an integrated manner enable a stronger defense against cyber threats. AI standardization ensures that security protocols operate according to specific rules and that systems can share data without harming each other.

- **Supportive Use of AI in Cyber Security:** AI facilitates the work of security teams by providing systems that can detect threats in the cyber security field more quickly and analyze them accurately. Technologies such as machine learning and deep learning have the capacity to predict attacks in advance and optimize defense mechanisms.

- **Harmful Use of AI in Cyber Security:** The misuse of AI can lead cyber attackers to develop more sophisticated and effective attacks. AI's potential to orchestrate attacks faster, more covertly, and more effectively can give rise to new types of threats. In particular, autonomous attack systems and AI-powered malware can render security measures inadequate against evolving threats.

Evaluating these three dimensions of AI use in cyber security reveals not only the potential benefits of these technologies, but also the risks they pose. This situation makes AI's role in security a double-edged sword, demonstrating AI's capacity to strengthen cyber security while also revealing its potential to create greater threats when misused. Therefore, establishing ethical guidelines and robust oversight mechanisms is crucial for the effective use of AI in cyber security (Mıjwıl et al., 2022).

The Relationship Between AI-ML-DL

The concepts directly related to the structure of AI are machine learning (ML) and deep learning (DL) components. The relationship between these three is critical for detecting and resolving threats at different levels in cyber security. Generally, AI is often used to detect potential threats by working on large data sets, while ML algorithms analyze past attack patterns to predict future threats. Deep learning, on the other hand, is used to strengthen cyber security systems by learning new and unknown threats that traditional methods cannot detect. The interaction between these three areas is critical in strengthening cyber security solutions with their complementary features (Kumar et al., 2025).

The relationship between these concepts can be explained as follows (Chua et al., 2025):

- **Artificial Intelligence (AI):** Artificial intelligence is an engineering discipline that aims to design machines and software with human-like thinking and problem-solving abilities. AI enables computers and machines to make decisions like humans and perform complex tasks such as understanding language, visual recognition, executing voice commands, and playing games.

- **Machine Learning (ML):** Machine learning is an AI subfield that enables machines to learn from data without being explicitly programmed. In other words, machine learning systems learn from experience by analyzing data and recognizing patterns without human intervention. In this process, algorithms and mathematical models are used to train machines to perform specific tasks increasingly well.

- **Deep Learning (DL):** Deep learning is a subset of machine learning that bases the learning process on a multi-layered structure using artificial neural networks. Deep learning algorithms use deep neural networks to extract more complex and abstract features from data. These networks are designed based on the human brain's learning process, learning deeper and more meaningful features at each layer.

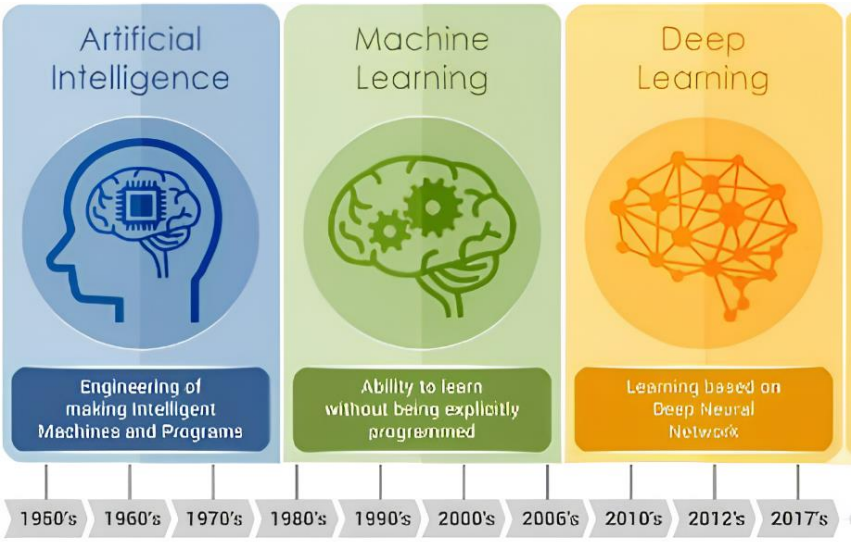

Figure 1. AI-ML-DL Relationship (Chukwunweike et al., 2024)

Industrialization Process and the Evolution of Threats

The industrialization process has led to significant transformation in the field of cyber security, just as technology and automation have reshaped the workforce, production, and processes. This change has also caused cyber threats to evolve. As a result of this expansion, the components related to cyber security have also changed over time. These fundamental components are used in the context of taking protective measures for system security, and developing defense strategies against these threats (Taj & Zaman, 2022).

These components, also known as the CIA triad, are explained as follows (Alomari et al., 2025):

- **Confidentiality:** Confidentiality ensures that only authorized individuals or systems can access data. This concept, which aims to keep sensitive information such as personal data, trade secrets, or government information confidential, is achieved through methods such as encryption, authentication, and access controls.
- **Integrity:** Integrity refers to the preservation of the accuracy and consistency of data. Data integrity must be checked and security measures implemented to prevent the manipulation of files, databases, or network communications.
- **Availability:** Availability refers to the ability of systems, data, and services to be used by authorized users when needed. Strategies such as backup, disaster recovery plans, and network load balancing are used to ensure availability and guarantee system continuity.

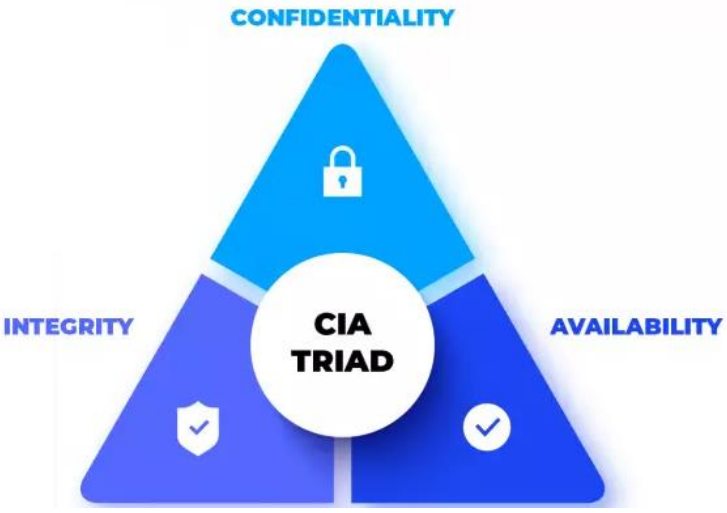

Figure 2. CIA Triad (ID Strong, 2024)

The rapidly evolving industrial structure in the context of cyber security has brought new challenges, but AI's adaptive capabilities enable more proactive prevention of cyber security threats while minimizing the need for human intervention. The combination of these technologies enables the development of more flexible, dynamic, and effective defense strategies that go beyond traditional methods in cyber security (Karasoy & Gezici, 2023).

Risk and Power Multiplier

The cyber security-AI relationship can be used both as a cause of risk and as a deterrent factor in the implementation process due to its two-way impact. On the one hand, AI-based systems enable real-time analysis of expanding attack surfaces through functions such as network mapping, asset visualization, and threat detection. On the other hand, the misuse of AI technologies can lead to more sophisticated and rapidly adaptive attacks, making cyber defense systems more difficult and complex (Kayode et al., 2025).

In this context, AI's role in cyber security can be positioned as either supportive or harmful, depending on its intended use, as a risk and force multiplier under the following components (Banerjee et al., 2024):

- **Faster Detection:** AI enables faster response to attacks thanks to its ability to detect cyber threats and risks in real time.
- **Network Security:** AI continuously monitors network traffic, detects suspicious activity, and makes intrusion detection systems more dynamic, enabling rapid adaptation to new threats.
- **Phishing Detection:** AI detects phishing attacks by analyzing fake emails and websites. It protects users from social engineering attacks by alerting them to such threats.
- **Secure Authentication:** AI enhances security by using biometric data and behavioral analysis in user authentication processes. These methods help prevent weak passwords and identity theft.
- **Behavior Analytics:** AI detects abnormal activity by analyzing user behavior and provides early warnings for security breaches.
- **Prevention Online Fraud:** AI analyzes transactions to detect online fraud and identify suspicious activity.

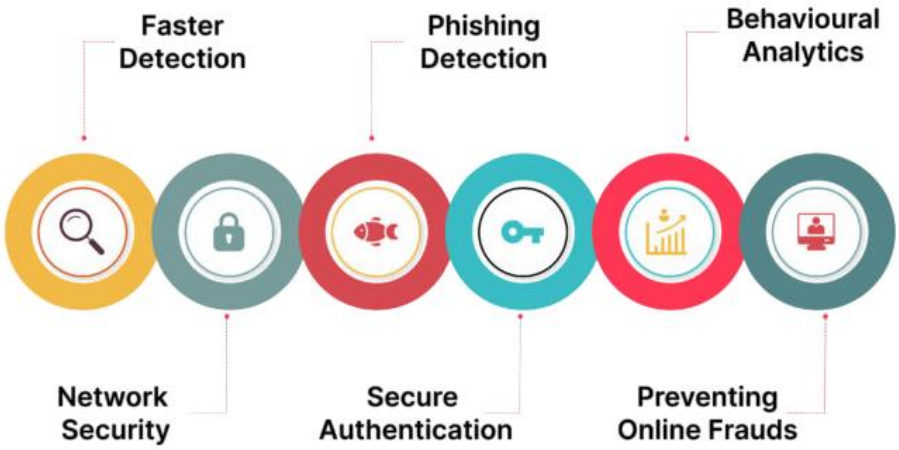

Figure 3. AI Role in Cyber Security (Banerjee et al., 2024)

As a result, AI's role in cyber security is shaping up to be both a powerful defense tool and a factor that makes potential threats more complex. While AI technologies play a critical role in protecting organizations against existing threats, they also carry the risk of misuse. Therefore, the secure and careful integration of AI and machine learning should be a fundamental element for the success of cyber security systems (Efe, 2021).

Risk Identification, Assessment, and Response Systems

The revolutionary change brought about by AI technologies in the field of cyber security has enabled the development of stronger, faster, and more effective defense strategies against threats. The capabilities offered by AI not only detect attacks but also enable rapid and proactive responses to these attacks. In this context, AI's applications in cyber security provide speed, accuracy, and flexibility in key areas such as threat detection, incident response, proactive defense, and user behavior analysis, enabling the development of a robust protection ecosystem against cyberattacks (Vadisetty, 2024).

The main application areas of artificial intelligence in the process of defining cyber security strategies and determining roadmaps are as follows (Chowdhury, 2025):

- **Unparalleled Threat Detection:** AI stands out as a tool that significantly enhances threat detection in cyber security. In particular, the use of machine learning and deep learning algorithms provides the ability to extract meaningful patterns from large data sets and classify them.

- **Swift Incident Response:** Cyberattacks create rapidly spreading threats that race against time, and responding quickly to these threats is critical to the success of defense strategies. AI plays a significant role in accelerating incident response once attacks are detected.

- **Proactive Defense:** AI lays the foundation not only for defense but also for a proactive security strategy in cyber security. Traditional security approaches are often limited in predicting threats before attacks occur.

- **Enhanced User Behavior Analytics (UBA):** User behavior plays a significant role in defense strategies against cyberattacks, as many attacks occur through individual users' misconduct against security policies. AI has the capacity to analyze this user behavior and detect non-normative activities.

Figure 4. Benefits of AI in Cyber Security (Mohammed, 2023)

Real-Time Intrusion Detection Systems

Real-time intrusion detection (IDS) is considered one of the critical processes in ensuring a fully functional cyber security ecosystem. The necessity of detecting cyberattacks before they cause significant damage to systems is met by the development of a series of technological components that enable the immediate analysis of potential threats and rapid intervention. The effectiveness of such systems is measured by their ability to be fed with accurate data and to classify threats correctly (Mohale & Obagbuwa, 2025).

IDS methods not only detect attacks but also assess the extent to which the system is affected by the attack. This is where machine learning algorithms come into play, analyzing similarities by comparing attacks with previous examples. Real-time detection requires threats to be quickly identified and evaluated, making it crucial for systems to be continuously monitored and able to make predictions based on historical data in this context (Martin & Zimmermann, 2024).

The following situations should be focused on during the development process of AI-based real-time attack detection systems (Beg et al., 2023):

- **Lack of AI Competence:** The lack of cyber security professionals specializing in AI makes it difficult to effectively manage these technologies and properly address potential threats.

- **Unmanaged Model Drift:** Training AI models with large datasets from various, uncontrolled sources prevents a complete understanding of how the model behaves and what it learns. This uncertainty can lead to a loss of reliability and make it difficult for the model to be an effective tool for cyber security.

- **Lack of Transparency:** The fact that AI systems are mostly “black box” structures makes it difficult to understand how their outputs are obtained. This lack of transparency poses a risk, especially in security decisions and incident response.

- **Autonomous Content Generation:** AI's ability to generate new content without human intervention can potentially lead to the spread of harmful or misleading information. This situation creates risks of misinformation and cyber manipulation while increasing security vulnerabilities.

- **Evolving Frameworks:** The rapid advancement of AI technologies has not been matched by the creation of adequate regulatory frameworks. This situation can pave the way for the misuse of AI and make it difficult to manage these technologies safely.

- **Increased Risk Tolerance:** Businesses' high interest in AI technologies and their desire to quickly embrace their potential benefits may lead to the use of these technologies without adequately assessing the risks they pose. This haste can increase organizations' risk tolerance by overlooking privacy and security vulnerabilities.

Machine Learning Algorithms

ML has been a major turning point in detecting and assessing threats in the field of cyber security. With its ability to identify potential threats by extracting meaningful patterns from large data sets, it can also recognize previously unseen or unlabeled threats. This advantage enables security systems to operate more dynamically and continuously adapt to new types of threats (Mian et al., 2024).

One of the most powerful features of ML is its ability to continuously learn and adapt. This advantage allows systems to quickly adapt to evolving attack techniques over time. Particularly in applications like anomaly detection, machine learning systems learn about network traffic, user behavior, and system activity by analyzing them, and quickly detect deviations. From this perspective, ML systems strengthen organizations' security strategies by detecting not only existing threats but also unknown threats (Amuru et al., 2023).

Another important area of application for these algorithms in the cyber security sphere is the development of predictive analytics and proactive defense strategies. ML systems can predict the possible effects and consequences of future threats by examining past attack patterns. These predictions enable security teams to prepare for future attacks and shape their defenses in advance, allowing them to determine the most appropriate security measures for each threat based on its severity and type. Today, ML methods can analyze the nature of attacks and generate automated responses against rapidly spreading threats (Dash et al., 2022).

Ultimately, ML's role in cyber security goes beyond threat detection and assessment. This technology not only enables the development of defense strategies more quickly and effectively but also allows for the continuous strengthening of security infrastructures. ML's adaptive and proactive features help cyber security teams build more robust and resilient defense strategies. This enables organizations to build a more resilient and secure infrastructure against evolving threats, thereby making their cyber security strategy development processes more efficient (Kuzior et al., 2024).

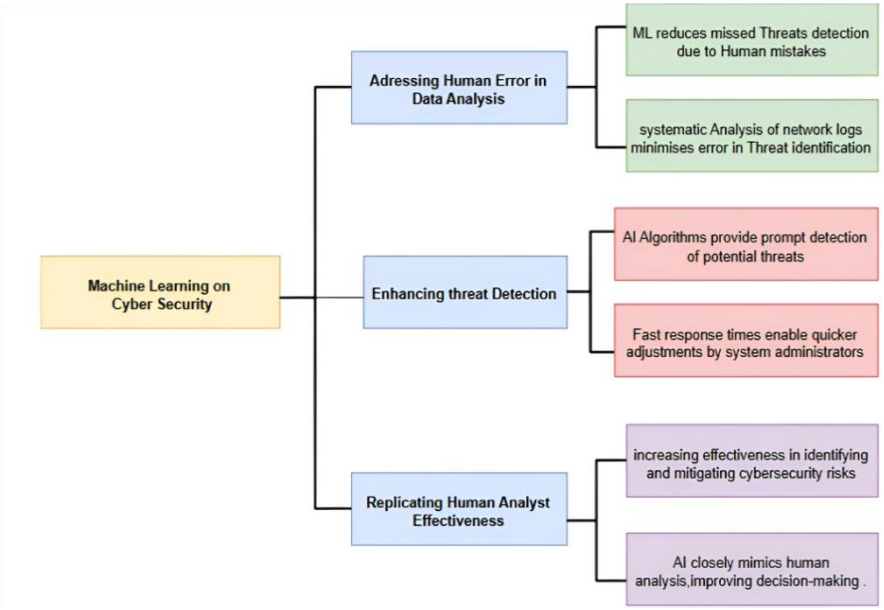

Figure 5. Impact of ML on Cyber Security (Chouraik et al., 2024)

Some common machine learning algorithms used in creating an AI-based cyber security environment and developing an integrated ecosystem are as follows (Salem et al., 2024):

- **Decision Trees:** Decision trees are an algorithm that classifies data by splitting it into branches. They can classify malicious activities with high accuracy by analyzing network traffic and user behavior.
- **Support Vector Machines (SVM):** Support vector machines are an algorithm that optimizes the separation between classes. Used for anomaly detection, they provide high accuracy in correctly distinguishing threats in networks and systems.
- **K-Nearest Neighbors (KNN):** KNN is an algorithm that classifies data points based on their similarity to neighboring points with similar characteristics. It is used to detect internal threats and unusual user behavior.
- **Naive Bayes:** NB is an algorithm that performs classification using a probabilistic model and assumes that each feature is independent. It is used to quickly identify types of attacks in applications such as email spam filtering and malware detection.
- **Artificial Neural Networks (ANN):** ANN are algorithms that enable data processing with multi-layered structures. They are widely used in AI-based threat detection systems to learn complex attack patterns and make accurate predictions through in-depth analysis.
- **Random Forest:** Random Forest is an ensemble learning method consisting of multiple decision trees. It enables threat detection by classifying anomalies and malware in network traffic.
- **Logistic Regression:** Logistic regression is an algorithm capable of binary classification and modeling the probabilities between classes. It is often used to distinguish between attack and normal states, particularly to quickly detect low-complexity threats.
- **Genetic Algorithms:** Genetic algorithms are algorithms that mimic evolutionary processes to find the best solution. They are used to predict attackers' tactics and optimize defense strategies.
- **XGBoost (Extreme Gradient Boosting):** XGBoost creates a powerful and efficient ensemble of decision trees and operates with high accuracy. It is used to quickly and accurately detect malware and cyberattacks by analyzing anomalies obtained from large datasets.
- **Clustering Algorithms:** Clustering algorithms classify data by grouping it based on similarities. They are used to detect deviations in user behavior and monitor attacker activities; they are generally suitable for internal threats and abnormal network movements.

From an organizational perspective, these capabilities of ML algorithms also play a significant role in strengthening organizations' security infrastructures. The algorithms analyze large data sets such as network traffic, user behavior, and system activities to identify anomalies and potential threats at an early stage. However, given the rapidly changing nature of threats, the adaptive structure of machine learning algorithms enables them to continuously adapt to new types of threats. This allows organizations to adopt a more dynamic and proactive security strategy and create a live defense network against attacks (Mohamed, 2023).

Reflex Demonstration Technologies

Reflex demonstration technologies are implemented as part of the risk assessment process to measure the impact of threats in cyber security and intervene accordingly. These systems analyze the potential impact of threats on the organization and enable security measures to be taken according to priorities. AI, ML, and DL technologies have the capacity to quickly detect threats in large data sets. AI-supported risk assessment not only analyzes existing threats but also enables preparation against possible attacks (Sun et al., 2024).

The primary function of reaction systems is to minimize the impact of attacks by enabling a rapid, simultaneous response to detected threats. These systems can take measures such as automatically restricting network traffic or blocking access to suspicious IP addresses. AI automates these interventions, reducing the risk of human error and enabling a faster response to incidents. In this regard, the integration of risk assessment and reaction systems used during and after an attack strengthens organizations' cyber security strategies, offering a more proactive and flexible approach (Bhavik et al., 2024).

Table 1. Threat Area-Reaction Type Relation in AI-based Cyber Security

Threat Area	Reaction Type
Intrusion Detection and Response	Supervised learning methods, such as Random Forest, SVM and neural networks are used to classify network connections as normal or anomalous.
Malware Detection	Unsupervised learning methods, such as Clustering and anomaly detection, are used to group similar malware together and detect new and unknown malware.
Network Security	Supervised and Unsupervised learning methods, such as neural networks, Random Forest and SVM, are used to detect network-based attacks and intrusions.
Security Automation	Rule-based and Machine learning techniques are used to automate repetitive and time-consuming tasks such as vulnerability scanning and and incident response.
Threat Intelligence	Unsupervised learning methods, such as Clustering, are used to group similar threats together and identify new and emerging threats.
Security Management	AI-based systems can be used to improve security operations, incident response and incident management, through automation and incident analysis.
Anomaly Detection	Unsupervised learning methods, such as density- based clustering and one-class SVM, are used to detect unusual or malicious activities in the network or system.
Cyber-attack Prediction	Supervised learning methods, such as Random Forest, SVM and neural networks, are used to predict cyber- attacks by identifying patterns and anomalies in network traffic.
Vulnerability Management	AI-based systems can use techniques such as rule-based systems, decision trees and clustering to scan systems and networks to identify potential vulnerabilities.
Security Education and Awareness	AI and ML can be used to create personalized and interactive security training content that is tailored to the specific needs and knowledge level of the individual.
Antiviruses with ML/AI Algorithms	Many antivirus software programs use AI and machine learning algorithms to detect, evaluate, and take necessary precautions against malware infections.

Source: Mohamed (2023)

Defense Approaches and Security Architectures

The increasingly important role of AI technologies in the current state of cyber security is creating revolutionary changes in the evolution of security architectures. AI's ability to analyze massive datasets containing millions of pieces of data enables it to quickly detect potential threats, identify abnormal behavior, and develop automated responses to these threats. This is particularly vital in developing integrated and robust security architectures against sophisticated attacks and unknown threats (Folorunso et al., 2024).

AI-based defense approaches also have a profound impact on the core components of cyber security: threat detection, preemptive measures, incident response, and continuous improvement processes. ML is used to more accurately identify security vulnerabilities and potential threats through techniques such as anomaly detection and behavioral analysis. Furthermore, AI dynamically updates security defenses by adapting to new threats and attack vectors through its continuous learning capability. This provides defenders with a critical advantage in today's rapidly changing digital environment (Alomari et al., 2025).

AI-powered security architectures are integrated, concurrently operating systems with the ability to work together, offering flexible and scalable solutions that generally strengthen organizations' cyber security infrastructure. These architectures can consist of multiple layers that can monitor the entire network structure and detect potential threats. Therefore, AI makes security systems more autonomous while also providing the necessary data and insights for systems to make accurate and timely decisions. This holistic approach can prevent attacks from spreading and greatly enhances organizations' security posture .In this regard, AI-based defense approaches and security architectures form an important foundation for the future of cyber security strategies. Compared to traditional security measures, AI-based systems identify and analyze threats faster, making effective intervention processes more efficient. As a direct result, AI applications in cyber security have become a critical tool for building a more secure future in the digital environment. (Basani, 2021).

Figure 6. AI-Based Cyber Security Architecture Elements (Davies, 2025)

Proactive Defense Strategies

Proactive defense strategies are gaining increasing importance as an approach that enables the prediction of potential threats and attacks in advance and the preparation of countermeasures during the development process of AI-based cyber security strategies. While traditional defense methods typically focus on detecting and responding to attacks, proactive defense strategies rely on identifying security vulnerabilities before attacks occur and taking preventive measures against these threats. This approach aims to create a more secure environment through advance preparations and rapid interventions, rather than merely reacting after an attack. AI and related technologies enhance the effectiveness of these strategies by enabling continuous monitoring of systems and networks and dynamic analysis of threats (Kazi et al., 2025).

On the other hand, it is possible to categorize the actions of cyber attackers, which lead to the creation of an advanced cyber security network, according to certain criteria such as their objectives, methods, scope, capabilities, or the magnitude of the damage they cause. The motivations of cyber attackers are generally shaped by financial gain, information theft, system disruption, or political and ideological goals. Attackers always aim to exploit the weakest points and develop strategies targeting vulnerable systems. Therefore, an insufficiently developed system can easily be manipulated by cyber attackers, causing much greater, lasting, and serious damage than expected (Özgül & Demirbaş, 2025).

The relationship between a cyberattacker's status as a threat actor and their source of motivation is shown in the table below:

Table 2. Cyber Threat Actor-Motivation Relation

Cyber Threat Actor	Motivation
Nation States	Geopolitical
Cybercriminals	Profit
Hacktivists	Ideological
Terrorist Groups	Ideological Violence
Thril-Seekers	Satisfaction
Insider Threats	Discontent

Source: Canadian Centre for Cyber Security (2020)

In this regard, proactive defense strategies play a critical role in cyber security, not only in terms of defense but also in preventing attacks and mitigating their effects. Technologies such as AI, ML, and DL are crucial in creating an advanced security infrastructure by increasing the applicability of these strategies. By adopting a proactive defense approach, they can build a strong wall for organizations in the digital environment, where the nature of threats is constantly changing, thereby helping to establish a long-term security strategy (Beg et al., 2023).

Security Architectures

Security architecture is the entirety of structures and processes used to protect an organization's information systems. These architectures provide protection against external threats while also managing internal security risks. Modern security architectures include different layers such as network security, database security, application security, and endpoint security. Security architectures also combine different security measures and monitoring systems for each layer, serving as a deterrent solution to protect organizations against potential attacks. In this regard, factors such as effective operability in each layer of security architectures and the ability to quickly detect abnormal behavior in network traffic are decisive in AI-based systems (Mushtag et al., 2025).

In this context, the layers and components of the security architecture are as follows:

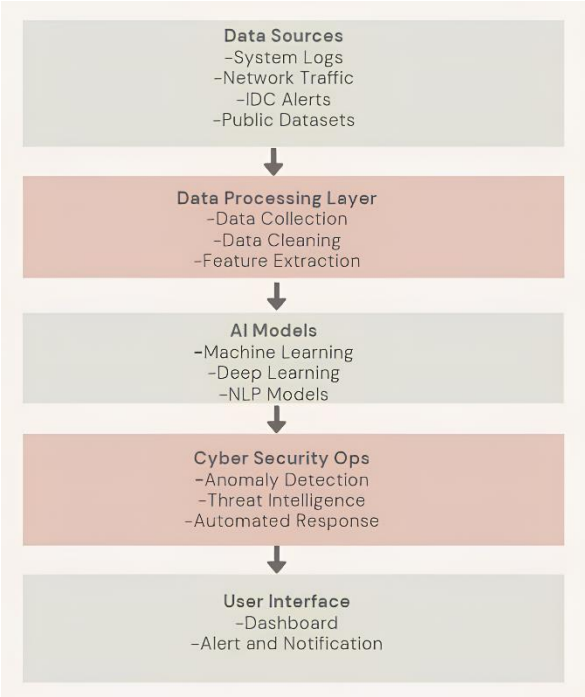

Figure 7: AI-Based Cyber Security System Architecture (Basani, 2021)

Data sources, one of the fundamental components of security architectures, collect data from networks, systems, and applications through various sensors and logs; The data processing layer refers to the process of processing, cleaning, and analyzing this raw data; AI models refer to AI algorithms used in cyber security to detect and predict threats; Cyber Security Ops refers to the security operations team responsible for continuously monitoring and effectively managing these processes; and User Interface refers to the interface that visualizes AI results and makes decisions based on this data (Vadisetty, 2024).

Therefore, security architectures not only provide defense against attacks but also ensure that organizations' security strategies continuously evolve. The integration of AI technologies and these multi-layered defense strategies used in the design of security architectures offer different solutions against threats at each layer, contributing to segmentation and manageability (Malatji & Tolah, 2025).

Integrated Security Technologies

Integrated security technologies are services that enable organizations to build more effective defenses by ensuring that different components of the cyber security infrastructure work together seamlessly. These systems combine firewalls, intrusion detection and prevention systems (IDS/IPS), antivirus software, and network security tools to create a multi-layered and coordinated defense structure. This allows each security layer of the system to play an active role against evolving threats over time. As a result, each security layer of the system plays an active role in combating threats by gaining a more comprehensive threat detection and response capability thanks to the information received from other layers (Akhtar & Rawol, 2024).

The necessary stages of AI technologies in the design of integrated security technologies, based on process-outcome continuity, are as follows (Freitas et al., 2025):

- **Data Gathering**: The data gathering phase is one of the fundamental steps of the AI ecosystem and is critical for detecting security threats. This phase involves the collection of information from various data sources, such as network traffic, system activities, user behaviors, and threat data from external sources.
- **Data Processing**: The data processing phase is the process by which collected data is transformed into meaningful and usable information. This phase involves cleaning the data, verifying its accuracy, and addressing missing or erroneous data.
- **Data Handling**: The data handling phase ensures the secure storage and protection of the collected and processed data. This phase guarantees the confidentiality and security of data, ensuring that only authorized users have access to it.

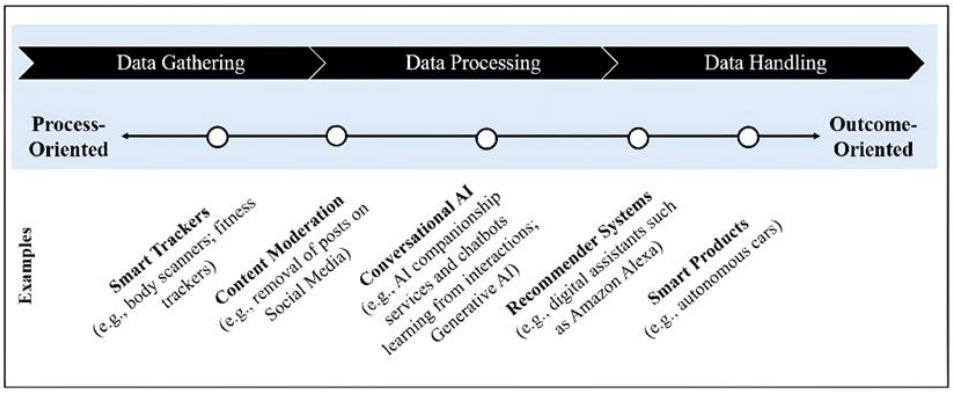

Figure 8. Process-Outcome Continuum of AI Technologies (Martin & Zimmermann, 2024)

In terms of performance, integrated security technologies are a critical component that enhances the success of cyber security strategies. The organic connection between AI-ML-DL significantly boosts the effectiveness of these technologies, enabling systems to respond to threats more quickly, accurately, and dynamically. In conclusion, integrated security architectures are considered one of the fundamental components ensuring continuity in the AI-based cyber security ecosystem; they enhance the effectiveness of defense strategies while also offering a more adaptable defense mechanism against attacker strategies (Anantrasirichai & Bull, 2022).

From Core to Ecosystem: AI-Driven Cyber Security Applications

In today's digital world, AI-powered cyber security applications are among the most important tools enabling faster, more accurate, and effective detection of cyber threats. These applications can identify threats that security experts cannot detect using traditional methods, employing techniques such as big data analysis and machine learning. Therefore, to develop a truly robust and dynamic cyber security network, it is an unavoidable necessity that every technology containing even a trace of AI is produced in a form that is compatible with all systems, capable of coordinated action, open to simultaneous information sharing, and able to take immediate action, from the design and implementation phase onwards (Kuzior et al., 2024).

Next-generation AI-based technologies also have a greater-than-expected impact on risk management processes in cyber security. The supportive algorithmic structure of these technologies allows for the early analysis of threats and the creation of appropriate strategies by addressing problems in development phases and improving decision-making processes. The high accuracy of algorithms in identifying vulnerabilities and classifying attack types by learning from past attacks and data facilitates rapid and accurate response to attacks, especially in large and complex networks, by reducing the need for manual security interventions (Goyal et al., 2023).

In this context, a framework for AI-based cyber security applications has been outlined, considering all elements of the AI lifecycle and supply chain, including relevant actors, processes, and technologies. The layers and features of this framework are summarized as follows (FAISP, 2025):

- **Layer I:** This layer covers the core cyber security knowledge and practices that must be applied to all IT environments hosting, operating, developing, integrating, maintaining, supplying, and providing AI systems. Existing cyber security best practices presented in this layer can be used to secure the IT environment hosting AI systems.

- **Layer II:** The second layer assumes that AI systems are supported by a reliable hardware infrastructure and focuses on the characteristics, threats, risks, and relevant tools and regulations of such systems. This layer encompasses the cyber security practices required to address the uniqueness of AI components in terms of their lifecycle, characteristics, threats, and security controls.

- **Layer III:** The final layer includes various applications that industry stakeholders can use to secure AI systems. High-risk AI systems are designed according to the AI regulations used in standardization and framework setting, and are consciously planned for situations encountered or likely to be encountered from the moment applications are deployed.

Within this framework, establishing appropriate infrastructure and processes for the effective operation of AI-based cyber security applications is a necessity rather than an option. To fully leverage the potential of AI-enabled cyber security applications, adaptable and appropriate regulations must be created to accommodate the nature of these developments (Sun et al., 2024).

Global Perspectives

The concept of cyber security is becoming increasingly comprehensive and critical globally, is constantly evolving with the rapid development of the digital technologies. Today, from a holistic perspective, cyber security has become a focus not only for individual organizations but for entire societies. In this context, the design, development, and applicability of AI-powered cyber security technologies must be considered as a whole and continuously improved in order to produce effective solutions (Taherdoost, 2025).

In this regard, the perspective that those controlling the top-level management network should have for AI control in the cyber security concept is explained as follows (Dash et al., 2022):

- **Director Education:** Aims to ensure that top-level managers understand the potential risks, opportunities, and strategic importance of AI technologies for the effective management of AI use in cyber security.
- **Threat & Opportunity Awareness:** Refers to being aware of AI's capacity to detect threats and evaluate opportunities in cyber security, and enabling organizations to effectively utilize the strategic advantages that AI-based technologies can offer.
- **Regulations & Disclosure:** Ensuring compliance with legal regulations regarding the use of AI and regularly reporting on the impact of AI on security strategies by organizations in accordance with sectoral and regional regulations.
- **Board Readiness:** Explaining how organizations can become more resilient against future threats by assessing their readiness to integrate AI into their cyber security strategies.

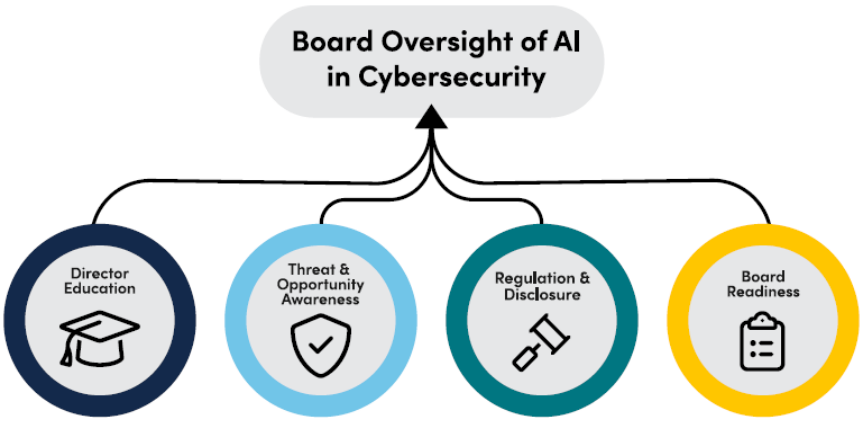

Figure 9. Oversight of AI in Cyber Security (NACD, 2024)

Overall, collaboration between different security infrastructures and threat detection systems worldwide is essential for a stronger defense against global cyber security threats. The ability to work together with AI-powered systems enables data sharing and faster response times, making it possible to develop common strategies in global cyber security practices (Bhavik et al., 2024).

AI Based Cyber Security Ecosystem Applications

Sector-specific cyber security is an approach developed to address the unique threats and security needs faced by organizations in different industries. Since each sector carries its own specific risks and threats, cyber security solutions must also be developed to cater to the unique requirements of these sectors. Within this context, the uses of AI-powered cyber security applications in different sectors are as follows (Freitas et al., 2025):

- **Healthcare**: Used to analyze patient health data, protect personal health information, and detect potential data breaches in real-time.
- **Telecommunications**: Used to monitor network traffic flow, identify abnormal behavior, strengthen network security, and respond rapidly to attacks.
- **Automotive**: Used to monitor in-vehicle systems and detect threats early to ensure cyber security in connected vehicles.
- **Manufacturing**: Used to analyze data from devices and machines on production lines, detect potential cyberattacks, and protect manufacturing processes.
- **Defense**: Used to protect military networks and critical systems, detect cyberattacks early, and quickly implement security measures.
- **Finance**: Used to analyze payment transactions to detect fraudulent activities and monitor suspicious activities in real-time.
- **Marketing**: Used to analyze user behavior and identify potential risks such as fraud, identity theft, and payment security issues.
- **Energy**: Used to analyze network traffic in energy infrastructures, detect cyberattacks, and ensure the security of energy resources.
- **Education**: Used to analyze student data and academic systems to secure network infrastructure and protect against potential cyberattacks.
- **Public Sector**: Used to protect government networks, safeguard critical information against cyber espionage, and prevent data breaches.

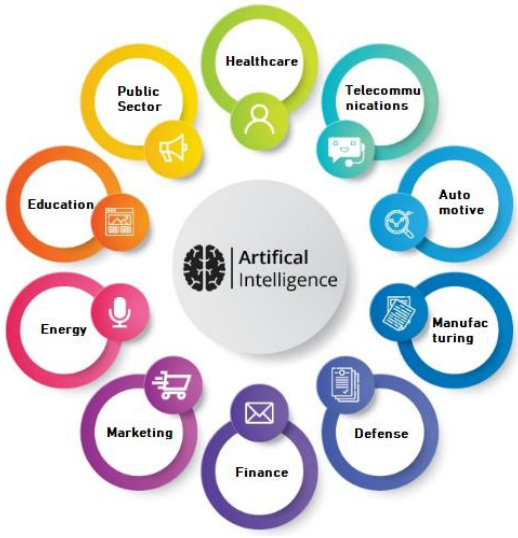

Figure 10. AI Based Cyber Security Applications Used Industries (Zhang, 2024)

Future Projections

It is believed that, as a necessity of the digitalized world, cyber security solutions will be shaped by the rapidly evolving technology of AI, leading to more dynamic, learning-based, and adaptable security systems. As technology becomes an integral part of daily life, cyber threats are becoming increasingly complex. As a result, AI technologies will not only detect these threats but also develop intelligent strategies for responding to attacks. Naturally, this process will make cyber security operations more proactive, enabling systems to respond more effectively to rapidly evolving threat environments (Kaur et al., 2023).

From the perspective of AI development, it is expected that the future role of current technologies in cyber security will not be limited to threat detection alone, but will also aim to dynamically optimize security strategies. This development will play a major role in the development of fully automated security ecosystems that enable security experts to make accurate and rapid decisions, integrating decision support systems and minimizing manual interventions (Kayode et al., 2025).

While adapting to this technological rise will have many advantages, failing to keep pace will have significant negative consequences. In this regard, the potential risks that may arise when common cyber security practices cannot meet the security requirements of AI systems are as follows (Nair et al., 2024):

- **Dynamic Risk Assessment**: AI-driven risk assessments should be dynamic, responding quickly and accurately to sudden events, and should be integrated with anomaly detection approaches.
- **Ethical Scaling**: Measuring AI threats and evaluating AI risks will require the development of a scaling system that meets common social and ethical values and is widely accepted.
- **Attacker Classification**: There is a need for an AI-driven classification of attackers that will enhance existing classifications to better understand their motivations, capabilities, targets, and psychological profiles.
- **Requirements Set**: Evaluating an AI product based on a static set of requirements can quickly become outdated. Therefore, dynamic risk management and compliance assessment throughout the entire AI lifecycle are necessary.
- **Multidisciplinary Approach**: Multidisciplinary Approach: AI systems are multidisciplinary socio-technical systems. Collaboration among stakeholders is necessary to identify the constantly evolving AI threat landscape and develop corresponding countermeasures.
- **Technology Selection**: Among various AI types, machine learning and deep learning undoubtedly present the greatest security challenges, requiring dynamic analysis of threats both throughout the lifecycle and in the relationships between the components of an IT infrastructure.
- **Bias Management**: AI-specific risk assessment studies must account for the unique characteristics of AI and should aim to prevent loss of transparency, bias management, and accountability while enhancing robustness, resilience, fairness, and explainability.

To provide complete protection against the stated risks, ensure real-time monitoring, and create a dynamic ecosystem, the following AI-based cyber security solutions should be used (NACD, 2024):

- **High-Quality Data:** High-quality data is critical for the accurate and effective operation of AI systems. This data must not only be meaningful for the application but also correct and reliable to ensure security. In high-risk AI applications, the quality of the data is a fundamental element that ensures correct detection of cyber security threats.
- **Continuous Monitoring:** High-risk AI applications require continuous monitoring to detect potential threats at an early stage. This process involves regular testing and auditing to ensure the security of the system before and after the deployment of AI. Continuous monitoring helps identify possible security vulnerabilities and close gaps in the system.
- **Risk Assessment:** Comprehensive risk assessments should be conducted before deploying AI systems. These assessments should focus on potential threats, vulnerabilities, and possible impacts, outlining necessary measures to secure the system. Risk assessments should be carried out in close collaboration with the organization's AI management team.
- **Technical Documentation:** AI-driven security solutions should be supported by proper technical documentation based on the continuous monitoring process. This documentation should include risk mitigation measures and the results of tests, providing guidance for all users. Additionally, AI practitioners should conduct their own tests to enhance system security.
- **Ensuring Transparency:** The licensors and licensees of AI systems should transparently share the capabilities and limitations of AI with users. This transparency helps users understand the limitations of AI systems and prevents uncertainty or misunderstanding regarding security issues. Furthermore, transparency enables users to take the appropriate security measures.
- **Human Supervision:** Human supervision plays a critical role in ensuring the security of AI systems. This supervision detects deviations from expected behaviors and ensures that the system returns to secure parameters. Responsible personnel within the organization should be able to intervene in AI systems and take corrective actions when necessary.
- **Kill Switch:** A kill switch should be implemented in AI systems in case of deviation from security parameters. This safety mechanism functions as an emergency shutdown button, preventing the AI system from operating uncontrollably. The kill switch ensures that the system can be safely shut down when corrective measures cannot be implemented.

Strengthening Human-AI collaboration will emerge as a key element determining the success of future cyber security solutions. In this context, AI-based cyber security systems will not only detect threats but also adapt to constantly evolving security threats, learning about new attack types more quickly. As a result, future AI-based cyber security applications will help create a more dynamic, flexible, fast, updatable, and integrated security ecosystem and strategies, customized to the diverse needs of each sector and enabling the creation of a robust defense architecture (Xu et al., 2025).

Acknowledgements or Notes

Disclosure of AI usage

During the preparation of this work, the author(s) used [ChatGPT] in order to generate text, check grammar, analyze data, or assist with literature search. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published work.

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Chapter 5- Artificial Intelligence in Visual Design

Murat Çoban & Yasin Sepil

Chapter Highlights

- Artificial intelligence (AI) is not merely a production tool in visual design; it is an interactive creative partner that reshapes the design process, making the designer's roles in problem definition, aesthetic guidance, and critical evaluation more central.

- While generative AI-based tools offer significant opportunities in terms of aesthetic diversity, speed, and experimental production, they also bring limitations such as aesthetic repetition, contextual inadequacy, data-driven biases, and copyright ambiguities.

- The use of AI in visual design redefines divergent and convergent thinking processes; AI particularly increases the diversity of ideas, while the processes of meaning-making and final decision-making remain dependent on the human designer.

- AI-assisted design practices accelerate the transition from individual creativity to new production models based on human-machine collaboration, making it necessary to re-examine the ethical, pedagogical, and professional boundaries of the design profession.

- A sustainable and responsible integration of AI in the field of visual design; Based on critical awareness, ethical sensitivity, and an interdisciplinary approach, this should be considered a shared responsibility of practitioners, researchers, and educators.

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Introduction

The rapid advancements in information and communication technologies driven by digital transformation are profoundly transforming production processes and creative practices in the field of visual design. AI-based systems, in particular, enable the re-imagining of visual design processes not only through automated production capabilities but also through creative reasoning, visual analysis, and design proposal mechanisms (Zou, Zhang & Zhao, 2025). In this context, AI is becoming both an instrumental support and an integral component of the creative process in visual production disciplines such as graphic design, illustration, digital art, and user interface design. Despite the widespread adoption of AI applications in visual design, comprehensive studies that holistically explain and theoretically discuss the effects of these technologies on creative processes are still limited. While AI is mostly considered a technical tool in the literature, a systematic examination of critical issues such as originality, creativity, and designer identity remains lacking (Mirzaei, 2025). This situation further highlights the importance of questions regarding the extent to which AI-supported visual productions can be considered ‘creative’ and how they transform the essence of design.

Furthermore, the integration of generative AI technologies into visual design processes raises ethical and copyright issues at both academic and professional levels (Karaman, 2025). In this new process, where designers interact with algorithmic suggestions alongside their traditional creative skills, redefining the designer's role and sharing creative responsibility has become an important area of research. In this context, discussing the role of AI in visual design on a theoretical and critical basis is necessary both to contribute to the academic literature and to create an informative framework for designers and educators.

The aim of this book chapter is to address the applications of AI technologies in visual design from an interdisciplinary perspective; to discuss the effects of these technologies on the design process, the designer's role, and creative production in conceptual, applied, and critical dimensions. While focusing on the aesthetic possibilities offered by AI-assisted production tools, creative collaboration models, and transformations in design processes, the study also aims to evaluate the limitations of these tools and the paradigms they create in both professional and educational settings (Karaman, 2024).

Applications of AI Technologies in Visual Design: An Interdisciplinary Perspective

The increasing use of AI technologies in visual design is transforming design processes not only technically but also cognitively, aesthetically, and culturally. This transformation positions visual design at the intersection of different disciplines such as computer science, cognitive psychology, art theory, and human-computer interaction, making design practice an interdisciplinary field of production. In particular, the visual content generation capacity of generative AI systems presents a new paradigm that questions the traditional human-centered structure of the design process (Manovich, 2019; Elgammal, 2021).

One of the most visible applications of AI in visual design is the support given to visual production and ideation processes. For example, AI models that produce visuals from text offer numerous alternative visual suggestions in the early stages of the design process, expanding the designers' thinking space. A graphic designer can quickly

experiment with different color palettes, compositions, and stylistic approaches for a poster design; this creates a faster and more experimental design environment compared to the traditional sketching process. However, in this process, AI does not define the design problem; It functions as a tool that generates possibilities in line with a defined problem. Therefore, the creative decision-making process still relies on the designer's conceptual and critical evaluations.

The integration of AI technologies into visual design also brings about a transformation of the designer's role. In traditional approaches, the designer is directly in a decisive position in all stages of visual production; in AI-assisted design, this role takes on a guiding and evaluative character. For example, in a user interface design process, AI can offer automatic layout suggestions based on usability data; however, the designer is responsible for evaluating these suggestions in terms of context, cultural meaning, and user experience. This situation shows the emergence of a new creative model based on human-machine collaboration (McCormack et al., 2019).

From an interdisciplinary perspective, AI-assisted visual design applications are not limited only to aesthetic production but also redefine cognitive processes and the concept of creativity. Studies in the field of cognitive sciences reveal that creative thinking consists of multiple processes of trial, feedback, and restructuring rather than a single moment of production. AI can support this cognitive process with its capacity to provide rapid feedback and generate variation; however, higher-level cognitive skills such as meaning-making, context-building, and critical evaluation remain unique to human designers (Boden, 2016). Therefore, AI is positioned not as an actor replacing creativity, but as an aid in structuring the creative process.

As a concrete example, when looking at the use of AI in the field of digital art, it is seen that artists, rather than directly exhibiting algorithmic productions, rearrange these outputs and place them within a conceptual framework. Images produced by AI often function not as the final product, but as an intermediate material that gains meaning through the artist's aesthetic and intellectual intervention. This situation reveals that originality in visual design is related not only to visual difference but also to conceptual context and intention (Elgammal, 2021).

On the other hand, AI-assisted visual design applications also bring significant limitations. The fact that these systems largely rely on existing datasets increases the risk of repetition and similarity in design. In commercial design applications in particular, the rapid proliferation of similar visual styles can weaken the distinctiveness of design. Furthermore, ethical issues such as copyright, transparency of data sources, and algorithmic biases have led to visual design practice becoming an interdisciplinary field of ethical debate (Floridi et al., 2018).

Consequently, AI technologies in the field of visual design cannot be considered either a completely independent creative force or merely a neutral tool. Rather, these technologies should be considered as a socio-technical actor that transforms the design process in its cognitive, aesthetic, and ethical dimensions. From an interdisciplinary perspective, AI's contribution to visual design is not so much a replacement for human creativity as it is an interactive space that reconstructs and expands it. This approach provides a more balanced and critical ground for academic discussions on AI in the field of visual design.

The Impact of AI Technologies on the Design Process, the Designer's Role, and Creative Production

The integration of AI technologies into the field of visual design is fundamentally transforming the structure of the design process, the role of the designer, and the nature of creative production. In particular, the widespread use of generative AI-based tools has transformed design practice from a purely technical production process into an interdisciplinary research field with cognitive, cultural, and ethical dimensions (Choudhury et al., 2025). This transformation necessitates a rethinking of both the theoretical foundations and practical applications of design.

Conceptually, the impact of AI on the design process can be said to be related to the redefinition of the concept of creativity. In traditional design approaches, creative thinking largely relies on the designer's experience, intuition, and contextual knowledge. However, AI-supported systems learn from large datasets, generating alternative visual solutions and offering new possibilities, especially in the idea generation phase of the design process. Choudhury et al. (2025) emphasize that generative AI tools support the divergent thinking phase in the design process; however, the decisive role of the human designer continues in convergent thinking processes. Divergent thinking is a way of thinking that aims to generate numerous, diverse, and original ideas instead of focusing on a single correct solution to a problem, issue, or design need (Choudhury et al., 2025). It is one of the fundamental concepts in the creativity, design, and innovation literature. Convergent thinking, on the other hand, is a way of thinking that focuses on selecting the most suitable, effective, or correct option from among numerous possible ideas or solutions generated for a problem (Cropley, 2006). It is often discussed together with divergent thinking in the design, creativity, and problem-solving literature.

In an applied context, AI is positioned as a tool that increases efficiency and expands creative diversity in design processes. Especially text-to-image and image-to-image generation models allow designers to generate numerous alternatives in a short time. This accelerates the design process while also bringing about critical discussions on the quality of design decisions. (Fu et al.) (2024) revealed that the use of generative AI increases visual diversity in design outputs; however, in cases of overuse, designers' tendency to generate original ideas may weaken.

The impact of AI on the designer's role is addressed within the framework of the human-machine collaboration paradigm. Current literature shows that the designer's role is evolving from that of a "producing" actor to that of a "guiding, evaluating, and contextualizing" one (Fang et al., 2025). In this context, the designer becomes a decision-maker who critically filters the outputs provided by AI, evaluating them in terms of aesthetic, functional, and cultural appropriateness. This transformation necessitates a redefinition of the designer's identity in terms of cognitive and ethical responsibilities. From a creative production perspective, AI presents both opportunities and limitations in aesthetic production processes. Since AI systems largely learn from existing visual data, the originality and level of novelty of the designs produced are subject to debate. Some studies reveal that while AI-assisted design outputs are aesthetically pleasing, they have limitations in terms of cultural context and the production of deep semantic content (Liang, 2024). This raises the question of whether AI is a “partner” or merely a “tool” in creative production.

In the critical literature, AI-assisted design processes are also evaluated from ethical and professional perspectives.

The fact that the datasets on which AI models are trained contain copyright, representation, and bias issues obscures the ethical responsibility of design outputs (Tsao et al., 2025). Furthermore, the impact of AI use in design education on students' fundamental design skills is also discussed. Education-focused studies show that generative AI can support creative thinking in design education; however, when used without developing critical evaluation skills, it can increase the risk of superficial production (Lee, 2025).

In conclusion, AI technologies are transforming the design process, the designer's role, and creative production in a multifaceted way. This transformation is not limited to technical innovations alone; It also reshapes the epistemological, aesthetic, and ethical foundations of design. Therefore, it is of great importance that academic studies addressing the relationship between AI and design are conducted with an interdisciplinary, problem-centered, and critical approach.

The Aesthetic Possibilities, Limitations, and Transformations in Design Processes of AI-Aided Manufacturing Tools

The proliferation of AI-powered production tools in the design field is transforming visual production practices and the nature of the creative process in a multifaceted way. Generative AI-based systems, in particular, play an active role across a wide spectrum of the design process, from the early stages to the final output; this necessitates a re-evaluation of the aesthetic, cognitive, and cultural dimensions of design (Choudhury et al., 2025). AI is positioned not only as a technical tool but also as an active component of the creative process, leading to a redefinition of the relationship between the designer and technology.

The aesthetic possibilities offered by AI-powered production tools are particularly evident in terms of visual diversity and formal experimentation. Text-to-image and image-to-image production models enable designers to transcend conventional aesthetic boundaries by generating numerous alternatives in a short time. This situation supports the expansion of creative potential in the divergent thinking phases of the design process and allows designers to simultaneously evaluate different styles, compositions, and forms of expression (Runco & Acar, 2012). This aesthetic diversity offered by AI transforms the design process into a more experimental and exploratory structure.

However, AI-assisted aesthetic production also has significant limitations. Since these systems largely learn from existing datasets, the visuals they produce are often based on a recombination of past aesthetic trends. This makes the concepts of originality and innovation problematic and brings about critical discussions on the creative quality of visual outputs produced by AI (Cropley, 2006). Furthermore, algorithmic biases, uniformity in cultural representation, and inadequacies in contextual meaning production constitute the critical dimensions of AI-assisted aesthetic production. The integration of AI into design processes transforms creative production from an individual activity into a model based on human-AI collaboration. In current literature, the designer is defined as an actor who directs, evaluates, and contextualizes the outputs produced by AI (Cross, 2011). In this collaborative model, AI functions as a partner generating numerous alternatives, while the designer is at the center of critical evaluation and decision-making processes based on convergent thinking. This indicates that the designer's role has evolved from a producer to a selective and interpretive one.

The use of AI-assisted production tools also brings about a structural transformation of design processes. Traditionally linear design processes are evolving into a more cyclical, rapid, and iterative structure with AI. The boundaries between idea generation, sketch development, and prototyping stages are becoming increasingly blurred; designers can continuously restructure the process with instant feedback. When evaluated within the framework of Brown's (2008) design thinking approach, it is seen that AI-assisted tools strengthen the exploration and iteration dimensions of the design process; however, the human-centered structure must be preserved in the evaluation and decision-making stages.

In conclusion, AI-powered manufacturing tools are having a powerful impact on design, enhancing aesthetic diversity, transforming creative collaboration models, and restructuring design processes. However, the limitations and critical aspects of these technologies must be considered alongside their possibilities. When AI is viewed not as a designer replacement, but as a tool that supports and expands human creativity, it has the potential to make sustainable and meaningful contributions to design practice.

AI Applications in Visual Design

The integration of AI technologies into the field of visual design has led to radical transformations in the production, evaluation, and distribution phases of design processes. In particular, the widespread use of generative AI-based tools has made visual content production faster, more accessible, and more experimental, while redefining the designer-tool relationship. Today, AI-supported software is used not only as auxiliary tools but also as active components of the creative process in many subfields such as graphic design, illustration, concept art, user interface design, and brand visuals.

These software programs offer designers the ability to generate numerous visual alternatives in a short time, experiment with different aesthetic styles, and accelerate iterative design processes. However, along with these possibilities, significant limitations also arise, such as aesthetic repetition, limited contextual understanding, lack of customization, and uncertainties regarding copyright. Therefore, the evaluation of AI-supported visual design tools should be approached not only through their technical performance but also from a holistic perspective, considering creativity, level of control, ethical responsibility, and their impact on professional design practice.

In this context, a comparative examination of the advantages and limitations offered by AI-based software widely used in the field of visual design is of guiding importance for both professional designers and educational settings. The sample software and evaluations presented below aim to make visible the role of AI in visual design practices through concrete tools and to discuss the effects of these tools on design processes within a critical framework. These tools support different visual design needs such as graphic design, logo design, illustration, visual production, UI/UX, or content creation.

Table 1. Some AI Tools Related to Visual Design

Application Name	Web Address	Advantages	Limitations
Midjourney	https://www.midjourney.com	Produces highly aesthetic and artistic visuals; strong style coherence; effective for rapid ideation and concept visualization	Limited user control over fine details; operates primarily through text prompts; copyright and authorship issues remain unclear
DALL·E	https://openai.com/dall-e	Accurate interpretation of textual prompts; supports image variations and inpainting; accessible interface	Visual outputs may lack stylistic depth; limited control for professional-level refinement
Adobe Firefly	https://www.adobe.com/firefly	Seamless integration with Adobe Creative Cloud; trained on licensed data, offering greater commercial safety	Less experimental and expressive compared to open or community-driven models
Runway ML	https://runwayml.com	Supports both image and video generation; strong tools for motion graphics and multimedia design	Requires technical familiarity; performance and output quality vary across models
Canva AI (Magic Design)	https://www.canva.com	Extremely user-friendly; enables fast visual production for non-designers; efficient for repetitive tasks	Outputs tend to be generic; limited originality and creative depth
Stable Diffusion	https://stability.ai	Open-source and highly customizable; allows local deployment; strong community support	Requires technical setup and computational resources; output quality depends heavily on model tuning

As can be seen in Table 1, the evaluation of AI-powered visual design tools should be approached not only from the perspective of their technical performance, but also from a holistic viewpoint considering their impact on creativity, level of control, ethical responsibility, and professional design practice. In this context, a comparative examination of the advantages and limitations offered by AI-based software widely used in the field of visual design is of guiding importance for both professional designers and educational settings.

Conclusions

This study aims to reveal the multifaceted nature of this transformation by examining the effects of AI technologies in the field of visual design within the context of aesthetic possibilities, production processes, the designer's role, and creative collaboration models. While generative AI-based tools offer significant advantages in terms of speed, diversity, and experimental capacity in design processes, they have also brought the designer's roles of problem definition, aesthetic guidance, and critical evaluation to a more central position. In this context, AI is positioned not as an element that replaces the designer, but as a partner that expands and restructures the creative process.

However, the possibilities offered by AI-supported visual production tools also bring with them various limitations and controversial areas. Aesthetic similarity, lack of contextual awareness, data-driven biases, and uncertainties regarding copyright necessitate a critical evaluation of these technologies. Therefore, the effects of AI in the field of visual design should be considered not only from the perspective of technological progress but also in the contexts of ethical, pedagogical, and professional transformation. This approach will contribute to the sustainable and responsible structuring of AI-supported design practices.

Recommandations

Recommendations for Practitioners

It is recommended that professionals working in the field of visual design use AI-powered tools not as ready-made solutions, but as interactive tools that support and guide the creative process. It is important for designers to develop a critical control mechanism over AI outputs, prioritizing their aesthetic decision-making, problem-solving, and contextual evaluation skills. Furthermore, increasing professional awareness of copyright, originality, and ethical responsibility will ensure that AI-powered productions are aligned with professional standards.

Recommendations for Researchers

It is recommended that researchers focus on interdisciplinary studies that examine the role of AI in visual design processes not only through technical performance but also within the framework of cognitive processes, creative thinking styles, and human-machine collaboration models. In particular, empirical studies examining how AI-powered design processes are restructured within the context of divergent and convergent thinking can make significant contributions to the literature. In addition, comparative and longitudinal research evaluating the long-term effects of generative AI on aesthetic diversity and creativity is needed.

Recommendations for Educators

It is recommended that educators working in the field of design education integrate artificial intelligence tools into the curriculum not only through technical usage skills, but also through critical thinking, ethical awareness, and creative process management dimensions. Learning environments should be designed to enable students to consciously use AI-supported production tools by fostering problem identification, aesthetic evaluation, and conceptual depth. This approach will contribute to the development of future designers as professionals who can consciously and creatively collaborate with artificial intelligence, rather than competing with it.

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Chapter 6- The Utilization of Artificial Intelligence in the Domain of Content Creation within Digital Media

Adem Özdemir

Chapter Highlights

- The advent of artificial intelligence technology has enabled the expeditious and efficacious generation of content.
- The advent of artificial intelligence technology has led to a marked enhancement in the professionalism of visual production when compared with human production.
- The advent of artificial intelligence technology has precipitated a paradigm shift, giving rise to a plethora of innovative features.
- The utilization of artificial intelligence technology has the capacity to enhance the quality of content produced from lower-quality content.

Introduction

Developments in information technologies have also brought about a radical change in the world of communication. Especially the innovative solutions obtained with artificial intelligence carry with them the potential for a major transformation in the media and communication sector. The use of artificial intelligence technologies in disciplines such as marketing, public relations, and advertising offers communication professionals the opportunity to carry out their work more effectively and efficiently. Artificial intelligence finds its place in many different areas across the sector. Content production is at the forefront of these areas of use. Artificial intelligence has the capacity to produce content in many formats such as text, visuals, video, and audio. These produced contents are used in a wide range of applications, from news websites to blogs, from social media platforms to advertising campaigns (Çelik, 2022: 110).

Artificial intelligence technologies, which are beginning to be used in different sectors, are predicted to offer both advantages and disadvantages, especially in business processes. In this context, the idea is being voiced that the extent of the advantage or disadvantageous effect regarding new technologies will largely be shaped by individual preferences. The foundations of the future, full of uncertainties, are being built upon the ability to adapt to new technologies, a comprehensive perspective, and the capacity for innovative thinking. While artificial intelligence technologies have the potential to cause job losses in some work areas, they are progressing in a way that is particularly worrisome for press employees (content creators). However, in light of continuously changing and evolving technologies, journalists must demonstrate the ability to adapt to rapidly transforming conditions and sudden changes. Viewed from this perspective, artificial intelligence can be considered a support tool that will alleviate the increasing workload of press employees and help them perform multiple tasks more effectively, rather than being seen as a threat element (Coşan & Şahin, 2024).

Thanks to its integrated structure and advanced systems, artificial intelligence meets many needs of the advertising sector by offering a wide range of uses, from idea generation to audience segmentation, from content creation processes to insight analysis. Furthermore, artificial intelligence, which enables the automation of daily routine tasks, creates great efficiency by saving time and energy. In this way, professionals can find the opportunity to focus more on activities that require more creativity, contribute more effectively to the achievement of business goals, and create shared value between buyers and sellers (Shah et al., 2020, p. 3).

Innovative solutions are provided by generating content in various formats such as text, visual, video, and audio using artificial intelligence technology widely in areas like content production, data analysis, personalization, and automation. This generated content can be effectively utilized in various media such as news websites, blogs, social media platforms, and advertising campaigns. For example, news articles can be created, product descriptions prepared, or social media posts designed with artificial intelligence. In the field of data analysis, the power of artificial intelligence is demonstrated in its ability to provide critical insights regarding the target audience by deeply examining large datasets. Such data enables marketing campaigns to be planned and executed in a more strategic manner. For instance, artificial intelligence technologies can be leveraged to identify customer segments with the potential to be interested in a specific product or service (Yengin & Çakar, 2024).

The concrete representations of these examples are shown in Figure 1 and Figure 2. The visual used in the content production titled "The Rise of Videocast Broadcasting: The New Star of New Media" is indicated in Figure 1.

Figure 1 The visual in question was created with the assistance of artificial intelligence (Newslabturkey, 2024)

Another example is the image generated for the news titled "SEO in news publishing: increase your ranking with competitor analysis" as shown in Figure 2.

Figure 2 Visuals Used in AI-Generated News (Newslabturkey, 2024)

In recent times, there has been a rapid rise in applications supporting the simultaneous execution of content creation, message delivery, and visual design processes, particularly in advertising activities. In this context, advanced technology solutions like ChatGPT and Midjourney are widely favored by many advertising agencies due to their advanced capabilities. ChatGPT, demonstrating human-like performance thanks to its natural language processing competence, can offer effective content suggestions for a successful advertising campaign (Zhang & Kim, 2023) and adds value to advertising processes with the texts it generates.

On the other hand, Midjourney enables the transformation of input texts into visuals and, with this feature, can prepare current and creative advertising visuals within seconds. Such applications, which mediate the conversion of texts or words into visual outputs, create a highly innovative paradigm in the advertising discipline. A thorough examination of these systems has the potential to establish a significant foundation for the broader application of intelligent technologies in the future of the industry (Çeber, 2024).

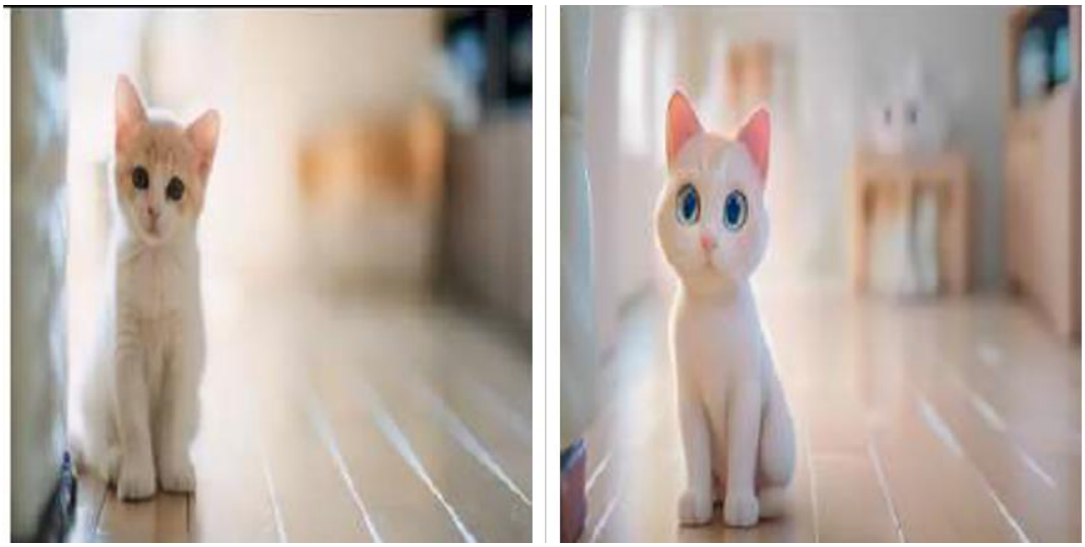

Figure 3 Image output generated from a real image using artificial intelligence

Artificial Intelligence Technology and Content Creation

Artificial intelligence technology is among the things mentioned as a new technology recently and followed with great admiration. The fundamental reason why artificial intelligence deeply affects human life dynamics is that it has started to be used in almost every field. Before moving on to the concept of artificial intelligence, providing explanations about what intelligence is will contribute to a better understanding of this technology. There is no single, comprehensive definition agreed upon for the concept of intelligence. One of the main reasons for this is that all functions of the brain, like the universe, have not yet been fully discovered, and therefore the human brain cannot be completely deciphered (Arslan, 2020: 75). Artificial intelligence, on the other hand, is stated as a concept that exhibits characteristics like human intelligence but is based on a technological infrastructure. In this regard, Table 1 shows the conceptual historical development of artificial intelligence technology.

Table 1The Conceptual Historical Development of Artificial Intelligence Technology (Yengin & Bayrak, 2023b: 145-146).

Year	Developments
1957	Neüell, Simon, and Shaw wrote a program called 'General Problem Solver'.
1958	John McCarthy pioneered the development of the Lisp language
1961	James Slagle created the 'Saint Aziz' program, which can solve first-class level math problems in Lisp.
1962	Unimation, the first industrial robot company, was founded.
1963	Thomas Evans wrote a program called 'Analogy' that could answer questions on IQ tests. Julian Feldman and Edward A. Feigenbaum published 'Computers and Hugh', considered to be the first papers in the field of artificial intelligence.
1964	Danny Bobrow's research at MIT has shown that computers can solve basic and simple mathematical problems.
1965	Joseph Weizenbaum created 'Eliza', the first interactive psychiatrist program capable of conversing in English on any topic.
1969	The first international conference in the field of artificial intelligence has been held.
1971	The robotic arm developed by Terry Winograd was able to carry out the given commands.
1972	Alan Colmerauer developed the artificial intelligence language called 'Prolog'.
1978	Herb Simon won the Nobel Prize for his theory of 'bounded rationality' in the field of artificial intelligence.
1980	The American Artificial Intelligence Association has held its first national artificial intelligence conference.
1985	Harold Cohen developed a program called 'Aaron' that enables drawing on a computer.
1995	Systems known as intelligent agents have begun to be created.
1998	With the spread of internet technology, many AI-based programs have been made available to a wide audience.
2000	Interactive toy robots are now available for sale.

There is no single agreed-upon definition for artificial intelligence. The main reason for this is that artificial intelligence is a subject of research for many different disciplines. Indeed, each discipline defines artificial intelligence according to its own theoretical framework. According to Pallathadka et al., artificial intelligence is a technology that generally expresses artificial production; that can learn natural language, plan, perceive, and process information (Pallathadka, 2023).

So artificial intelligence has great potential in the field of personalization and offers the possibility of providing tailored experiences to each user. For example, by analyzing a user's past behavior and interests, personalized content recommendations can be made. In addition, thanks to the possibilities offered by automation technologies, artificial intelligence helps communication professionals use their time and resources more efficiently by automating many manual tasks (Yengin & Çakar, 2024).

Artificial intelligence is divided into four basic categories: reactive machines, limited memory, theory of mind, and self-awareness. Reactive machines have the capacity to develop a perspective on the situations they encounter but have no memory storage function. Therefore, they approach every problem as if they are encountering it for the first time, without any experience. Limited memory is involved in various applications and is generally used to provide specific alerts regarding events experienced by users. Theory of mind is a concept also frequently used in the discipline of psychology and plays a critical role in individuals' decision-making processes (Harranoğlu, 2024).

In other words, this means that the situation is connected to the emotional states of individuals, such as their beliefs and passions. In the context of personal knowledge, artificial intelligence indicates that this system possesses original thoughts. As a result, it can make inferences about the events it encounters based on its own thoughts (Aydın & Ektik, 2023).

One of the main advantages of artificial intelligence in content production is its ability to work quickly and with high efficiency. Artificial intelligence algorithms built on extensive text and visual datasets have the capacity to produce content much faster and more effectively than humans. Furthermore, content generated by artificial intelligence can be easily customized according to the characteristics of the target audience. This customization capability directly contributes to the produced content being more engaging and effective. In addition to speed and customization capability in content production, another significant advantage provided by artificial intelligence is its creative potential. Artificial intelligence can surpass the limits of human thought and present innovative and previously unimagined ideas. Thus, it becomes possible to design communication campaigns in a unique and impressive manner (Çelik & Karabıyık, 2024).

The increasing impact of digital technologies in all areas of life is also leading to significant transformations in the world of communication. Especially the opportunities offered by artificial intelligence herald a fundamental change in the media and communication sector. Artificial intelligence applications in professional fields such as marketing, public relations, and advertising enable communication specialists to carry out their processes in a more efficient and purposeful manner (Çelik & Karabıyık, 2024).

The value of generative artificial intelligence stems from its strong connection with natural language processing (NLP) technology. NLP combines linguistics with artificial intelligence, equipping computers with the ability to read and understand the natural languages spoken by humans (Anyanwu, 2011). Advertising professionals utilize NLP systems to analyze large datasets related to consumer preferences and behaviors. In this process, they are not only capable of generating personalized advertising messages consisting of various content types like visual, video, and text, but also ensure that such messages are created in alignment with user interests and preferences. Beyond text-based content creation, different elements such as images, video, and audio have become an integral part of the content generation process (Çeber, 2024).

Artificial intelligence has the capacity to design customized advertisements in real-time based on the data obtained. The integration of content production and personalization processes significantly increases the

effectiveness of advertisements (Gao et al., 2023). In this context, while agencies currently utilize various algorithms to accelerate content production and offer the right solutions to their clients, brands can enhance their tailored message design processes by using artificial intelligence applications as a supportive tool in the content creation process (Murár & Kubovics, 202).

Artificial intelligence has the capacity to create content in various formats, not just text, but also visuals, video, and audio. This generated content finds application across a wide spectrum, from news platforms to blog sites, social media channels, and advertising campaigns. Furthermore, artificial intelligence is increasingly important not only in content creation but also in branding processes. Thanks to intelligent algorithms, brands can analyze their target audiences more deeply, build more meaningful and strong connections with them, and develop strategies that maximize customer experience. Artificial intelligence, whose impact in creative industries grows every day, has become a fundamental component of this transformation (Çelik & Karabıyık, 2024).

The Advantages Offered by Artificial Intelligence in Content Creation

Decryption or audio transcription applications are defined as the process of converting an audio file into written text, and this process significantly consumes the time of journalists in particular. In this context, reporters have the opportunity to speed up their work processes and save time by utilizing artificial intelligence-based technologies that can quickly and effectively transcribe audio files into text. However, to ensure the highest efficiency in this process, it is important that the audio recording is clear and background noise is kept to a minimum. Furthermore, it is recommended that these texts be finally checked manually to guarantee the accuracy of the texts generated by artificial intelligence; as in some cases, expression differences that may lead to spelling errors or shifts in meaning can occur.

On the other hand, artificial intelligence applications are not limited to facilitating transcription processes; they also offer the ability to convert text files into sound. At this point, the aspect to be considered is the accurate conveyance of features such as style and tone required for the presentation of news texts to the artificial intelligence system. As a further area of use, audio recordings generated with the help of artificial intelligence and personalized background music can be utilized in video shares accompanying categorized news. Such innovative applications both increase efficiency in the media sector and support the delivery of content to the audience with a professional presentation (Coşan & Şahin, 2024).

Content Generation: It offers the ability to quickly and effectively perform tasks such as preparing subtexts for the sharing of generated content in digital environments like social media and creating relevant keywords or hashtags. Internet editors can also simplify their processes by using artificial intelligence as an assistant when needing to deliver trending content quickly. Furthermore, detailed work such as text editing can be supported by the capabilities provided by artificial intelligence. However, it is a critical point for press professionals to create the correct 'prompt' texts to obtain the desired results from artificial intelligence. A prompt is the method of directing correct and clear questions to the machine to obtain the desired outputs (Coşan & Şahin, 2024).

Visual editing is gaining attention as a process frequently used by journalists, especially in the context of social media platforms or online journalism. In this regard, innovations brought by artificial intelligence (AI) technology offer the possibility of performing these operations more quickly and efficiently. During the editing of photographs that reflect the essence of the news, rather than altering the reality of the visual, AI algorithms can be used to convert them into formats suitable for media platforms' requirements. In addition to AI seamlessly handling tasks like resizing visuals for social media posts, it is believed that this technology offers significant time savings for journalists in processes frequently used in online news, such as image compositing, background removal, and image extension. Furthermore, it has become possible to enhance low-quality news photographs using AI to give them a more professional appearance. These innovative processes performed by AI aim to increase the effectiveness of visuals in journalism and provide significant technical contributions to press members. Moreover, it is considered that personalized image generation technologies can be utilized to protect against copyright issues for simple news content prepared on current and popular topics. These AI-powered solutions both open new avenues that encourage creativity in news presentation and optimize workflows in the industry (Coşan & Şahin, 2024).

Disadvantages of Artificial Intelligence in Content Creation

Although the development of artificial intelligence technology seems to have lightened the workload in human life, it is stated that it also has problems in some aspects. Some of these problems are as follows: (Anderson et al., 2018; Harrranoğlu, 2024).

- ***The human factor*** with machines replacing humans, has led to the delegation of decision-making processes to these devices. This situation has resulted in the reduction or complete elimination of elements such as independence and privacy.
- ***Data abuse*** mainly occurs when the data owners use the data they possess for purposes other than their intended use, in line with their own interests.
- ***Job loss*** is emerging as a significant problem in today's rapidly changing and digitalizing world. Particularly, the widespread adoption of artificial intelligence in many sectors and the acceleration of business processes due to the advantages provided by this technology are leading to a decrease in the need for human labor. This situation increases the risk of job loss for individuals working in areas that cannot keep up with technology or where automation has taken over. The conveniences offered by artificial intelligence cannot be ignored; however, this transformation in the labor market is also affecting individuals and societies very seriously.
- ***Dependency***, as artificial intelligence gains more functionality, may lead to the gradual weakening of individuals' personal skills and thus the need for smart machines to increase. In other words, it is predicted that becoming dependent on these devices in almost every area of daily life will be inevitable in the very near future. The impact of the conveniences offered by technology on human behavior may lead people to rely increasingly on artificial intelligence-based systems instead of developing their own abilities.

- ***Chaos,*** the incredible speed of progress in technology and digital applications today, lays the groundwork for the use of information as a weapon, and this situation creates serious effects on society. The deliberate spread of lies that distort the truth along with correct information, misleading propaganda, and manipulative content can cloud people's thinking world, making them dangerous both individually and on a societal level. Despite living in the information age, this situation paves the way for new generations of confusion and conflict arising from the misuse of information.

Result

It cannot be ignored that artificial intelligence technologies, especially in social media platforms, are dramatically changing their traditional operation, transforming them from being merely communication and interaction platforms between users into increasingly prominent commercial markets. In this context, artificial intelligence applications have shaped the processes of information circulation, users' overall experiences, and the social dynamics of these platforms in both positive and negative ways.

Artificial intelligence algorithms used in content moderation aim to protect platform users from potentially harmful content, while at the same time being criticized for their potential to deeply intrude upon user privacy. Similarly, predictive analysis and personalized advertising mechanisms make a significant contribution to increasing the efficiency and profitability of economic transactions conducted through social media platforms, but these approaches also emerge as new threats to user privacy, raising security and privacy concerns to higher levels (Lekshmi et al., 2024). At this point, it is of great importance that the content generated, especially when using artificial intelligence technologies in content creation, is accurate, transparent, and reliable.

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Chapter 7- Artificial Intelligence Applications in Businesses

Rafet Beyaz

Chapter Highlights

- Artificial intelligence (AI) is transforming businesses across various sectors, enhancing efficiency, speed, and flexibility.
- AI supports faster, more accurate decision-making through the analysis of business processes, customer interactions, data, and consumer trends.
- AI enables personalized customer experiences, sales forecasting, opportunity management, and automation of business processes in customer relationship management.
- AI contributes to product development, pricing decisions, supply chain optimization, and quality control in production processes.
- AI accelerates innovation cycles, enables data-driven decision-making, and enhances risk management in product development.
- AI optimizes inventory control, transportation networks, procurement processes, demand planning, and order fulfillment in supply chain management.
- Effective use of AI requires attention to ethics, data privacy, and human–machine collaboration to create long-term value for businesses.

Introduction

Industry 4.0, referred to in the English-language literature as the "Industrial Internet," can be defined in its broadest sense as the "internet of machines, computers, people, and things." This phenomenon is regarded as a collective term encompassing numerous contemporary automation systems, data exchange mechanisms, and production technologies (Özsoylu, 2017). The Industry 4.0 process represents a period marked by significant changes and transformations across nearly all sectors as a result of rapid technological development and the widespread diffusion of digitalization. In this process, innovative technologies such as big data, Artificial Intelligence (AI), the Internet of Things (IoT), and cyber-physical systems are integrated into business processes, thereby enhancing efficiency, speed, and flexibility. While Industry 4.0 symbolizes a new era that enables organizations to optimize their production and management processes, AI stands out as one of the most prominent technologies within this transformation (Sarnıç & Acar, 2024).

Artificial intelligence is generally defined as the capability of computer systems to perform human-like reasoning, learning, and action (Russell & Norvig, 2022). Broadly described as the "intelligence exhibited by machines" (Siau, 2017), AI refers to the ability of systems to correctly interpret external data, learn from such data, and use these learnings to flexibly adapt in order to achieve specific goals and tasks (Kaplan & Haenlein, 2019, p. 15). This concept is used to describe systems capable of performing human cognitive functions—such as reasoning, inference, generalization, and learning from experience—particularly in environments characterized by rapid change and high levels of uncertainty. AI does not rely solely on digital technologies; it also draws upon disciplines such as neuroscience. In this context, AI-based systems employ advanced algorithms capable of analyzing patterns and features within data, enabling learning as well as search and prediction based on that learning (Şahinbaş, 2025).

An examination of the historical trajectory of technology reveals that nearly all sectors have benefited from this phenomenon. In today's world, artificial intelligence is widely used across many fields. Numerous time-consuming tasks—such as accessing services, leisure and entertainment activities, monitoring routine and repetitive processes, and enriching educational activities—are carried out through AI-based tools. In this context, businesses, like other users of advanced technologies, increasingly benefit from artificial intelligence to save time and labor while achieving more successful outcomes. Although the level of adoption has not yet reached its desired potential, it is evident that a wide range of business activities are conducted with the support of AI tools (Berberoğlugil, 2023).

By enabling machines and software to mimic human intelligence through capabilities such as learning, problem-solving, and decision-making, artificial intelligence contributes to faster and more accurate decision-making, optimization of production processes, and increased customer satisfaction within organizations (Sarnıç & Acar, 2024). AI supports businesses in gaining competitive advantage by facilitating faster, more efficient, and more effective decision-making through the analysis of business processes, customer interactions, data, and consumer trends.

Moreover, AI tools allow organizations to conduct financial transactions, manage complex logistics processes, track technological innovations, and carry out various marketing activities. Within this framework, the benefits that businesses derive from AI tools can be summarized as follows (Karakulle & Aktepe, 2023):

- AI applications enable organizations to serve a larger number of customers simultaneously.
- AI applications provide the advantage of offering services to customers 24 hours a day, seven days a week.
- By structuring interactions between businesses and customers in an organized manner, AI applications enhance the overall customer experience.
- They allow customers to find desired products, monitor the supply process, compare different products, and complete payment transactions.
- They assist customers in contacting the relevant business units regarding complaints or information requests.
- They contribute to reducing labor costs and improving the quality of services provided.
- AI supports increased organizational efficiency, cost reduction, customer satisfaction, and employee performance.

As observed, artificial intelligence tools are widely utilized in the field of business administration, as in many other domains. Furthermore, the use of these tools in business activities generates numerous advantages. In this regard, it is considered beneficial to promote the widespread adoption of AI tools in business practices. Both academic and practice-oriented studies contribute to this process. Accordingly, this study focuses on widely used AI applications in businesses and their effects, and provides a synthesized evaluation of detailed assessments presented in various studies.

Artificial Intelligence Applications in Businesses

Artificial Intelligence in Management

Artificial intelligence is increasingly becoming an integral component of managerial processes in organizations. This phenomenon enhances organizational efficiency and strengthens leadership effectiveness by introducing various innovations in management and leadership practices. At the same time, in order to manage emerging organizational challenges, managerial levels are required to employ appropriate change management approaches and effective leadership structures. AI has brought about profound transformations across numerous sectors—from business and healthcare to education and manufacturing—and has generated particularly significant changes in the fields of leadership and management. In this context, developments such as accelerated decision-making processes, improved operational efficiency, and the emergence of new business models have been realized. For the effective implementation of AI in management processes, it is necessary to benefit from technological advancements such as big data analytics and automation (Akturan, 2024).

Chapter 7: Artificial Intelligence Applications in Businesses

In the field of management, artificial intelligence is commonly observed to be used through artificial neural networks as tools for decision-making and forecasting. Studies employing these methods have found that the results obtained are more accurate than those derived from analyses conducted using traditional statistical tools. Moreover, the use of AI-supported intelligent hybrid systems, agent-based systems, and computer-assisted systems in strategy development, planning, and management processes has become widespread. In this regard, a substantial body of research focuses on the use of artificial intelligence as a tool in knowledge management processes in particular (Ünal & Kılınç, 2020).

The integration of artificial intelligence (AI) with Decision Support Systems (DSS) significantly enhances the effectiveness of these systems through technologies such as data analytics, machine learning, and natural language processing. With the support of big data analytics and machine learning, managers have gained the ability to make faster and more accurate decisions. These systems can analyze historical data to identify trends that may emerge in the future. Such integration increases both the speed and accuracy of decision-making processes, while also enabling more efficient execution of data-driven processes. Through large-scale data analysis and predictive algorithms, AI provides managers with the opportunity to make more timely and well-founded decisions. In addition, AI is reported to make substantial contributions to decision-making processes in areas such as data analytics, scenario analysis, and risk assessment, thereby enabling managers to engage in more accurate strategic planning (Akturan, 2024).

Business management expert systems are AI-based applications designed to support managers' strategic decision-making processes. These systems play a critical role in determining organizational growth and competitive strategies. Furthermore, within the scope of business education, business management expert systems aim to equip instructors and students with the knowledge and skills necessary to succeed in the business world. In this respect, such systems are regarded as effective tools that foster analytical thinking skills for solving complex real-world business problems and support informed decision-making in the field of management. Some widely used examples of business management expert systems are presented below (İnceme & Öztürk, 2024).

BizManager: BizManager is an AI-supported application developed to support business management processes. The application is used in areas such as monitoring financial data, inventory management, customer relationship management, evaluation of organizational performance, and process optimization. In addition, Biz Manager can be effectively utilized in educational settings aimed at business management training, teamwork, and the development of collaboration skills. By enabling product inventory tracking, timely replenishment of stocks, monitoring income–expense balance, assessing financial status, organizing customer data, and analyzing customer needs, the system contributes to improving service quality.

Expert.ai: Expert.ai is an application that offers AI-based language solutions and adopts a scalable, powerful, and cost-effective approach. The system can be used for intelligent document processing, text annotation and labeling, model training, testing, and refinement processes. Expert.ai is widely applied in various fields, including document analysis in the legal sector, text mining in medical research, development of automated response systems in customer services, and risk analysis in the financial sector.

In addition, artificial intelligence can contribute to the more effective execution of leadership-related functions. The impact of AI on leadership is primarily examined under two main dimensions: its contribution to shaping managerial decisions and the support it provides for team management in digitalized work environments. Research indicates that AI-based systems enable leaders to process large volumes of data in a short time, identify patterns, and make decisions based on more robust information. Moreover, outputs generated by AI systems contribute to the development of leadership approaches that adapt more rapidly to changing conditions and encompass diverse employee groups. For instance, tools that analyze employees' emotional states can assist leaders in monitoring team motivation and developing strategies to enhance engagement levels. However, the literature also cautions that excessive reliance on AI applications may overshadow leaders' human judgment; therefore, it is emphasized that technological solutions should be used in conjunction with empathy, ethical evaluation, and human-centered decision-making processes (Akturan, 2024).

Artificial Intelligence in Human Resource Management

Human resource management (HRM) is a managerial field that aims to effectively plan, manage, and develop employees, who constitute the most valuable asset of organizations. Encompassing core processes such as recruitment, training, performance appraisal, compensation, and fringe benefits, HRM seeks to enhance employee potential in order to achieve organizational objectives and to create a positive work environment. In addition, as a business function, HRM aims to increase job satisfaction and motivation by fostering a supportive organizational climate. Effective human resource management not only strengthens organizational productivity and competitiveness but also reinforces legal and ethical compliance. Today, artificial intelligence applications contribute to increased employee satisfaction and productivity by making HR processes faster and more efficient (Uçar & Bulut, 2024).

In recent years, human resource departments have increasingly turned toward digital transformation, streamlining their processes by leveraging big data analytics, artificial intelligence, and cloud-based systems. In many organizations, digital technologies such as chatbots, machine learning applications, and robotic process automation are utilized in HR activities including recruitment, onboarding, candidate screening, and interviews. AI applications in human resources reduce administrative workload while improving candidate identification and talent acquisition processes. Moreover, these technologies contribute to predicting employee retention probabilities, reducing error rates, supporting process continuity, increasing employee engagement, and helping to mitigate bias in decision-making processes (Yawalkar, 2019, p. 23). Artificial intelligence is employed in various HRM functions, including personnel selection, training and development, career planning, compensation, and performance evaluation. However, it is observed that recruitment and talent acquisition processes are the areas in which AI solutions are applied most widely and effectively (Toprak, Özel, & Çalışkan, 2022). Within this scope, AI applications used in human resource management are applied in the following areas (Gür, Ayden, & Yücel, 2019; Gürsel, 2021; Uçar & Bulut, 2024):

- Recruitment processes: Many organizations utilize digital technologies to identify and evaluate candidates. AI-supported systems enable rapid screening of applications and allow timely feedback to candidates. In addition, chatbots and automated response mechanisms play a significant role in managing inquiries and requests related to the recruitment process effectively.
- Screening and interview stages: AI enables the analysis of written and verbal assessments and facilitates the conduct of digital interviews. Furthermore, intelligent scheduling tools simplify the organization of interviews and meetings, thereby enhancing the candidate experience.
- Reduction of administrative workload: AI-supported technologies automate repetitive tasks within HR units, alleviating operational workload and increasing process efficiency.
- Selection processes: AI applications analyze candidates' competency and skill profiles, allowing HR managers to identify suitable candidates in a shorter period of time.
- Reduction of discrimination: By minimizing subjectivity in evaluation processes, AI contributes to more transparent and consistent decision-making. It also supports the selection of candidates aligned with organizational objectives through the analysis of job descriptions.
- Enhancement of productivity: Artificial intelligence and robotic process automation undertake repetitive tasks such as data collection, reporting, data processing, and payroll management, thereby increasing workforce productivity in HR processes. These applications contribute to workload balancing and more efficient use of resources.
- Enrichment of learning: Digital technologies and AI-supported systems enable the management of training processes through data analytics and provide real-time feedback during learning activities. These tools support employee development, save time, and strengthen performance-based learning approaches.
- Employee training and performance management: AI-supported training systems analyze individual learning needs and offer personalized training content. By identifying methods appropriate to learning pace and style and ensuring the continuous updating of training materials, these systems enable employees to continuously enhance their competencies and contribute to organizational performance.
- Employee experience and satisfaction: AI applications allow for the continuous monitoring of employee satisfaction and work experience. AI-based feedback and analytics systems help organizations identify areas for improvement by determining employee expectations and needs. While sentiment analysis techniques examine employee feedback to measure motivation levels, chatbots and virtual assistants provide rapid responses to employee inquiries. In this way, timely feedback is delivered to employees and overall productivity is increased.

The use of artificial intelligence in human resource management enables processes to become more flexible, efficient, and employee-centered. By supporting employees' competencies and guiding career planning, AI facilitates more objective and unbiased evaluations. Moreover, by assuming routine tasks through automation, AI reduces the workload of HR units and allows employees to focus on more creative and strategic activities. The analytical capabilities of AI enhance the effectiveness of HR functions in areas such as predicting employee turnover risks and improving interview and recruitment decisions, thereby directly contributing to organizational performance (Kambur, 2022)

Artificial Intelligence Applications in Accounting and Financial Activities

In organizations, accounting functions consist of fundamental stages such as the collection, classification, recording, and reporting of financial information. These processes provide the data necessary for analyzing financial conditions and evaluating organizational performance, while also playing a critical role in strategic decision-making. Accounting is not limited to fulfilling legal obligations; it also contributes to organizational sustainability and growth by providing management and stakeholders with reliable, systematic, and transparent information. Within this framework, the effectiveness of the accounting system enhances organizations' capacity to safeguard their financial structures and plan for the future. Today, artificial intelligence technologies are transforming financial management by making accounting processes faster, more efficient, and more accurate, thereby supporting organizations in managing their financial structures more effectively (Uçar & Bulut, 2024).

The use of artificial intelligence technology can be evaluated in terms of the four core functions of accounting: recording, classification, summarization, and reporting. Through AI-supported recording functions, invoices can be automatically transferred into accounting systems via scanners, while classification, summarization, and reporting processes can be performed more rapidly and with fewer errors through advanced software programs. Moreover, by using AI technologies, financial statements can be analyzed through ratio, horizontal, vertical, and trend analyses; however, the interpretation of these analytical results still requires human expertise. Accordingly, accounting professionals are expected to play a more active role in consultancy and strategic decision-support processes rather than focusing primarily on routine tasks such as data entry, recording, declarations, and notifications (Gündüz, 2025).

Organizations are transforming their accounting processes by effectively utilizing AI-based accounting software for functions such as digital storage of documents, verification and tracking of invoice information, financial risk management, and monitoring of user activities. The adoption of such software contributes not only to increased productivity and operational efficiency but also to improved customer services, support for flexible working models, and optimization of human resource utilization. Through integration into operational accounting processes, the management of accounts payable and receivable becomes faster and more accurate, while effective debt management strengthens relationships between organizations and their suppliers. In addition, the transformation of traditional accounting methods into AI-supported digital systems increases efficiency by saving time and paper, and largely eliminates the problem of lost documentation (Sevim & Yılmaz, 2024).

Artificial intelligence applications have both positive and negative effects on accounting systems. Some of these effects are summarized as follows (Gündüz, 2025; Akpınar & Baskan, 2024):

In manual accounting processes, unintentional and unconscious errors may occur. AI-supported accounting systems can automatically detect such errors and ensure that records are maintained accurately and consistently. This enables accounting professionals to focus on higher value-added activities rather than data entry and verification.

- By automating accounting tasks and analyzing large-scale datasets, AI technology offers significant transformative potential in the accounting field. In particular, AI algorithms used in financial statement analysis learn patterns and relationships within large datasets, thereby assisting accountants and financial analysts in identifying potential risks more effectively and making more informed decisions.
- Advances in cognitive computing technologies and AI applications are leading to radical transformations in accounting and auditing. AI can address complex problems that are difficult to resolve through human effort alone. Numerous accounting procedures—such as order processing, invoicing, sales transactions, cost reporting, and the management of accounts payable and receivable—are expected to be improved through AI. It is anticipated that this technology will increasingly assume core functions in financial institutions, transforming operational practices to achieve greater efficiency and cost savings.
- One of the most advanced application areas of AI in the accounting discipline is the use and development of expert systems. Expert systems are designed to provide advisory support to accountants in various areas and possess the capacity to monitor and enhance cognitive and analytical processes.
- In addition to the aforementioned benefits, AI also presents certain disadvantages in this field. With the widespread adoption of AI technologies, employment in accounting and auditing professions may decline. In particular, the acceleration and simplification of processes related to the acquisition and classification of accounting data reduce the demand for personnel working in these areas.

Financial instruments and financial markets are among the areas most significantly affected by the transformation and evolution driven by artificial intelligence technology. The intersection of AI and financial markets is commonly conceptualized within the framework of Financial Technology (FinTech). With the emergence of FinTech, there has been a noticeable increase in both academic and practice-oriented studies in this domain. Systematic examination of this literature is important for understanding areas of concentration and the changes occurring within the financial system. FinTech, derived from the combination of the terms “finance” and “technology,” is a relatively new concept that refers to companies operating outside the traditional business models of financial institutions by utilizing technological tools in the provision of financial services, as well as the products and services they offer. More specifically, FinTech encompasses the digital delivery of financial services—such as payments, asset management, crowdfunding, lending, capital markets, and insurance—through innovative tools including the internet, mobile technologies, and data analytics (Yıldız, 2022).

One of the key areas in which artificial intelligence is applied within the financial domain is banking activities. AI applications are used by banks to obtain market intelligence, deliver banking services to customers more effectively, and facilitate communication processes. The use of AI in banking contributes to strengthening bank image, retaining existing customers, and acquiring new customers, while also encouraging customers to shift toward internet and mobile banking channels in order to reduce branch congestion and increase service delivery speed (Gümüş, Medetoğlu, & Tutar, 2020).

Artificial Intelligence Applications in Marketing

The marketing function in organizations plays a critical role in the effective delivery of products and services to consumers and in ensuring customer satisfaction. Marketing contributes to product development processes through market and competitive analyses, supports strategic decision-making, and enables the identification of target audiences. In addition, advertising and branding activities are carried out to increase brand awareness, attract potential customers, and boost sales. While these activities allow organizations to reach priority audiences and establish long-term customer relationships, artificial intelligence technologies make marketing processes more personalized and efficient, enabling clearer communication of messages to target groups and improving the overall customer experience (Uçar & Bulut, 2024).

One of the primary objectives of organizations is to conduct their daily operations in a sustainable manner in line with the principles of effectiveness and efficiency. In this regard, marketing teams in particular tend to adopt innovative and intelligent technological solutions in order to create a superior customer experience. The necessity of comprehensively understanding the expectations, behaviors, and needs of existing and potential customers has directed marketers toward the use of artificial intelligence (AI)-based platforms. In marketing, AI is defined as an approach that aims to predict customers' next behaviors and optimize the customer journey by leveraging customer data, machine learning, and similar AI techniques. Today, applications of AI in marketing are developing rapidly alongside the growing diversity of modern software and services available to brands. The increasing accessibility of AI technologies enables the emergence of diverse usage patterns in marketing activities and contributes to strengthening organizations' strategic decision-making processes by providing data-driven insights (Alkaddour, 2022).

It is evident that the use of artificial intelligence in marketing manifests through a variety of applications. Within this context, different uses of artificial intelligence in the field of marketing are evaluated in the following sections.

Artificial Intelligence in the Marketing Mix (4Ps)

Artificial intelligence, through its capacity to simulate cognitive processes inherent to human intelligence, is creating significant transformations in product development, marketing, and distribution processes. Owing to its big data analytics and predictive capabilities, AI is reshaping all stages of the product life cycle. Particularly during the idea generation phase, AI-supported insights that foster creativity enable more accurate analysis of emerging trends, consumer preferences, and market gaps, thereby allowing product ideas to be guided in a more informed and data-driven manner. AI-driven analyses provide product managers with the ability to identify consumer preferences, market gaps, and emerging trends, making product development processes more conscious and effective. By predicting customer preferences and automating and optimizing processes, AI reduces risks throughout the journey from ideation to market launch, while enhancing market fit and customer satisfaction. Moreover, generative AI applications support ideation and creativity, transforming innovation processes and providing organizations with a sustainable competitive advantage (Şahin & Şahin, 2024). In addition, AI-powered

analytical tools can systematically scan user-generated content on social media to analyze consumers' demands and expectations, thereby enabling production processes to be shaped through a customer-oriented approach. While social media data help organizations understand how products and services are perceived by consumers, these insights make it possible to develop campaigns aimed at building stronger consumer relationships (Campbell et al., 2020, p. 229).

In marketing planning, making accurate pricing decisions is of critical importance for organizations seeking long-term success. When determining a pricing policy for a product, various internal and external factors influencing the final price must be taken into account. Particularly in demand-based pricing approaches, real-time monitoring of fluctuations in demand and the timely adjustment of prices are essential. AI-based pricing systems enable real-time and dynamic pricing by considering changing market conditions. Through systems operating on machine learning principles, prices of products offered on e-commerce platforms can be rapidly and effectively updated by comparing them with the prices of the same products on competing websites (Gupta & Pathak, 2014).

AI-supported technologies contribute to cost reduction and increased delivery speed by optimizing supply chain and distribution processes. Innovative applications such as collaborative robots (cobots) and drone technologies offer significant benefits, particularly in terms of productivity and delivery efficiency. In addition, service robots developed with emotional AI enhance customer interaction in the retail sector and contribute to improving the shopping experience. However, for these technologies to be implemented effectively and sustainably, the human factor must not be excluded from processes, as maintaining customer satisfaction remains a critical requirement (Verma et al., 2021, p. 230).

Promotion management, one of the elements of the marketing mix, traditionally encompasses sales management, advertising management, public relations, personal selling, and direct marketing. With the digitalization of business processes, these elements have also undergone a comprehensive digital transformation. In a digitalized and constantly evolving marketing environment, the customer—who occupies a central position in the process—largely determines the content they wish to access, as well as the timing and channel of engagement. AI systems analyze data such as customers' profiles, preferred and disliked content, followed accounts, and subscribed communities, thereby enabling the implementation of personalized promotional policies for each individual customer. AI-based promotion systems can optimize content and messages delivered to customers in real time, while simultaneously monitoring and recording personal data obtained from customers through AI algorithms. In particular, netnographic research based on user-generated content—such as comments, likes, and follows on social media platforms—allows marketing professionals to structure their strategies and the algorithms they employ in a more effective and target-oriented manner (Özer Çizer, 2022).

Within promotional strategies, advertising is the area in which artificial intelligence is most widely applied. With the increasing use of AI and big data in advertising, personalized advertising practices have come to the forefront, and chatbots are used effectively to influence consumers' purchasing decisions. Through advertising content tailored to consumers' needs and preferences, online experiences are rendered more interactive and personalized via AI-supported systems. Today, in the advertising industry, AI is actively utilized in numerous areas, including

customer database management; targeting and personalization in advertising campaigns; analysis of consumer behavior; market research; content development; audio and visual advertising production; positioning of advertising messages and products to maximize consumer attention (neuro-advertising); optimization of advertising expenditures; and the design of online advertising experiences. In this respect, it can be stated that artificial intelligence has brought about a fundamental and cost-effective transformation in the advertising sector. Through AI-supported applications, the industry has evolved into a more measurable, target-oriented, and efficient structure (Başfırıncı & Koç, 2023).

Artificial Intelligence Applications in Customer Relationship Management (CRM)

The effective analysis and utilization of individual customer data has become a strategic priority for managers in today's business environment. In the era of big data, organizations are able to gain deeper insights into their customers through data collected from numerous touchpoints, including customer purchases, sales and service interactions, website and social media visits, satisfaction surveys, and payment processes. In this context, Customer Relationship Management (CRM) systems have emerged as a strategic tool that enables firms to deliver higher service quality, strengthen customer relationships, identify high-value customers, perform effective targeting, and develop personalized and cross-selling-oriented recommendations tailored to customer needs. Artificial intelligence has now been significantly integrated into many stages of the sales funnel, including activities such as email composition, calendar management, and lead management. Nevertheless, the fundamental objective underlying all AI-supported applications should be the development of customer relationships and the enhancement of long-term customer value (Gülşen, 2019).

Artificial intelligence is one of the most widely used new digital technologies in customer relationship management, allowing firms to gain a more comprehensive understanding of their customers and to improve the overall customer experience. Many organizations—particularly companies such as Amazon, Google, Netflix, and Facebook—analyze large volumes of data derived from customers' purchase histories, digital behaviors, and social media interactions through AI-based systems in order to deliver personalized services and enhance sales performance. The data that form the foundation of AI applications enable the generation of meaningful insights from online interactions, while software agents such as chatbots have become prominent tools in customer service by interacting with users through written and voice-based communication, thereby improving service quality and customer satisfaction. While chatbots typically respond to relatively simple requests and inquiries, virtual assistants—another AI application—are capable of delivering multifunctional services similar to those provided by human assistants. In this regard, the most widely used virtual assistants worldwide include Siri, Google Assistant, Amazon Alexa, and Microsoft Cortana (Esmer & Şaylan, 2021).

The integration of artificial intelligence with customer relationship management provides firms with several advantages. Some of these benefits are discussed below (Çakır, 2024):

- *In-depth Analysis of Customer Behavior*: Artificial intelligence enables the rapid and efficient analysis of large datasets, allowing for an in-depth examination of customer behavior. As a result, organizations can gain a more accurate understanding of customer preferences, habits, and needs, and obtain critical information—such as which products customers prefer or which types of campaigns they are more responsive to—thereby facilitating the development of more effective and targeted marketing strategies.
- *Personalization of the Customer Experience*: By analyzing customer data, artificial intelligence makes it possible to design personalized customer experiences. This allows firms to offer more tailored, meaningful, and need-oriented services, while particularly in e-commerce platforms, personalized product recommendations based on past purchasing behavior contribute to increased customer satisfaction and purchase likelihood.
- *Sales Forecasting and Opportunity Management*: Artificial intelligence supports sales forecasting and the more effective management of sales opportunities through the analysis of customer data. In doing so, it makes significant contributions to inventory management, campaign planning, and revenue enhancement processes.
- *Customer Sentiment and Rapid Feedback*: Artificial intelligence enables real-time monitoring of customer sentiment, allowing dissatisfaction and emerging problems to be identified promptly. By ensuring that this information is communicated to relevant teams in a timely manner, AI facilitates rapid intervention, strengthens customer relationships, and helps prevent negative customer experiences.
- *Automation of Business Processes*: Through CRM software, artificial intelligence enables the automation of business processes by handling routine tasks and allowing employees to focus on more strategic and creative activities. This enhances operational efficiency by automating repetitive processes and the routing of customer requests.
- *Customer Communication and Interaction*: Artificial intelligence enhances customer communication and interaction through chatbots and virtual assistants, providing customers with fast and effective support and contributing to improvements in service quality and customer satisfaction.

Artificial Intelligence in Brand Management

Artificial intelligence plays a significant role in the creative processes of brands. Utilizing AI technologies in the creation of visual and text-based content enables the development of creative and impactful materials that strengthen brand identity. AI contributes to faster, more consistent, and efficient content production by automating content generation processes. For instance, AI-based content creation tools are capable of producing various types of content, including blog posts, articles, and social media updates. In addition, AI supports brands in generating visual elements such as logos, websites, and other design components. AI-powered design tools provide creative ideas and suggestions to help brands enhance their visual identity (Çakmak, 2024).

AI is increasingly influential in product and brand management processes, assisting businesses in developing more competitive strategies. Through big data analytics and machine learning, organizations can analyze consumer preferences, purchasing habits, and expectations more accurately. This information provides a strategic foundation

for new product development, the improvement of existing products, and the formulation of marketing strategies. Moreover, AI plays a critical role in personalizing products and services, enabling the delivery of tailored recommendations and solutions to customers, thereby enhancing customer loyalty and brand value.
In production processes, automation and robotic systems improve product quality while reducing costs. In customer service, chatbots and automated support systems facilitate uninterrupted and rapid service delivery. Within this framework, AI makes product and brand management processes more effective and efficient, providing businesses with a substantial competitive advantage (Gündüzyeli, 2023).

Artificial Intelligence Applications in Production and Supply Chain Management

The production function in businesses refers to the process of transforming raw materials and other inputs into final products or services. This function encompasses stages such as production planning, resource management, and quality control. The primary objective is to ensure that products or services meeting customer demands are produced on time, at low cost, and at the desired quality level. Effective production management enhances efficiency, strengthens the firm's competitive advantage, and improves the ability to respond quickly and flexibly to market demands (Uçar & Bulut, 2024).

The integration of artificial intelligence creates significant transformation in product management in terms of innovation, efficiency, and market alignment. AI accelerates product development processes, particularly by increasing accuracy and speed in bringing new products to market, thereby shortening innovation cycles. Market research and consumer validation activities conducted during the transition from idea to market are made more effective through advanced data analytics. Product managers gain valuable insights into consumer behavior, preferences, and sensitivities, strengthening data-driven decision-making and enhancing risk management in product development (Şahin & Şahin, 2024).

One of the key areas in production significantly transformed by AI is design. AI reshapes design methods, decision-making processes, and the role of designers. Understanding this transformation is critical for predicting future design practices. The integration of AI into design processes transforms how design is executed through automation and data analytics, particularly enhancing speed and accuracy in optimization and routine decision-making. While technical decisions such as material selection and production methods can be supported by AI, creative, aesthetic, and user-focused decisions still require human intuition and experience. This has led to new approaches based on human–AI collaboration in design. Additionally, AI transforms fundamental design principles, adding a new dimension to user-centricity. By analyzing user data and predicting behavior, more personalized and user-oriented design solutions can be developed. AI-supported tools in user experience design enable more dynamic and flexible design processes through real-time feedback analysis. Moreover, the proliferation of AI accelerates processes, enables the creation of more complex solutions, and introduces new theoretical approaches regarding the role of design in driving innovation. This transformation reshapes the roles of designers and necessitates the reformation of design theory and education accordingly (Tatlısu, Bağlı, Turan, Hamurcu, Eser & Avcı, 2025).

AI can also serve as a strategic tool that enhances quality control activities, making them more reliable, sustainable, and competitive. Although control activities in businesses do not directly add value to the product, they play a critical role in ensuring product quality. With the increasing prevalence of automated production systems, quality control processes have also evolved into automated and AI-based structures. AI techniques are effectively used in various quality issues, such as detecting patterns in control charts, identifying foreign materials in products, and detecting surface defects and visual errors. Literature indicates that AI-supported quality control systems provide high accuracy and efficiency, accelerate control processes, save time, and significantly reduce operational costs (Kesici & Yıldız, 2016).

Artificial Intelligence Applications in Supply Chain Management

Artificial intelligence (AI) is transforming traditional practices in supply chain management, making processes more efficient, flexible, and sustainable. Effective management of the supply chain, which spans from production to distribution and involves multiple stages, requires accurate data collection, analysis, and integration into decision-making processes. AI meets these requirements through advanced data analytics and automation capabilities, accelerating decision-making, optimizing operations, and contributing to the holistic improvement of supply chain performance (Çelik, 2025).

AI-supported systems have a wide range of applications within supply chain management. These include inventory control and management, transportation network design, procurement processes, demand planning and forecasting, and order fulfillment (Akben & İnceacar, 2018).

From a planning perspective, AI applications contribute significantly to demand forecasting, inventory management, and order planning in supply chain management. Literature indicates that machine learning-based methods are more flexible and adaptive compared to traditional forecasting techniques, providing higher accuracy in the face of variable market conditions and uncertain demand structures. These approaches enable firms to respond more rapidly to demand fluctuations, plan stock levels more effectively, increase inventory turnover, and reduce stockouts. Consequently, decision-making processes are strengthened, and overall supply chain efficiency is significantly enhanced (Cannas et al., 2023).

AI also enhances transportation and logistics processes, improving efficiency and sustainability from route planning to delivery times. Route optimization reduces fuel consumption and logistics costs while shortening delivery times and minimizing environmental impact. Google’s AI-powered traffic algorithms exemplify this, helping logistics companies determine more efficient routes. Moreover, autonomous vehicles and drones hold potential for future transformations in logistics. AI also facilitates informed supplier selection by analyzing past performance and risk factors, and through natural language processing (NLP) and risk management applications, it can anticipate contractual issues and supply chain disruptions, enabling proactive solutions (Shabbir & Anwer, 2018; Mah et al., 2022).

In logistics, AI is commonly applied to delivery and returns processes. AI, particularly through NLP-based chatbots, automates order inquiries, pricing quotes, and other stages, accelerating delivery processes and supporting direct sales activities. Data mining applications optimize delivery methods, reduce logistics costs, shorten delivery times, and significantly enhance customer satisfaction. Furthermore, in returns and reverse logistics, AI supports circular economy practices by facilitating the management of uncertainties and complexities, offering more measurable, effective, and efficient solutions (Cannas et al., 2023).

AI also significantly contributes to inventory and stock management. Today, companies utilize AI techniques such as expert systems, artificial neural networks, fuzzy logic, and genetic algorithms to optimize stock levels. Literature demonstrates that these methods outperform classical approaches in demand forecasting, cost balancing, and determining optimal stock levels. Neural network-based models are particularly effective in the manufacturing sector, while fuzzy logic and genetic algorithms provide flexible and effective solutions for complex inventory problems. Overall, AI renders inventory control and management more practical, efficient, and effective (Akben & İnceacar, 2018). In general, AI provides substantial benefits within production and supply chain management. Some of these benefits and application areas are summarized in the table below (Bader, 2025).

Table 1: Benefits of Artificial Intelligence Applications to Supply Chain Management

Areas	Benefits
Planning	● Increased inventory turnover rate ● Reduced number of days without stock ● Optimal inventory control
Supply	● Increased accuracy in supplier selection and reduced processing time ● High accuracy rate in detecting defective products
Production	● Optimization in resource utilization ● Improvement in early fault detection ● Improvement in maintenance services
Distribution	● Reduction in proposal preparation time ● Effective communication with the customer ● Increase in proposal acceptance rates ● Improvement in customer satisfaction ● Reduction in transportation costs
Returns	● Reduction in inventory transportation costs ● Reduction in location costs ● Improvement in customer service ● Automation and increased speed in return processes ● Increased environmental sustainability

Conclusion

This study highlights the multidimensional transformation brought about by artificial intelligence (AI) applications in businesses and comprehensively evaluates the strategic impacts of these technologies on management processes. The findings indicate that AI makes decision-making faster, data-driven, and more predictable; it enhances operational efficiency, reduces costs, and improves customer experience. AI-supported applications in core business functions such as production, supply chain, marketing, and customer relationship management play a crucial role in securing competitive advantage. At the same time, the effective and sustainable use of AI requires attention to ethics, data privacy, and the human factor. Consequently, AI should be considered not merely as a technological tool, but as a strategic transformation element that, when approached through human–machine collaboration, can create long-term value for businesses.

Notes

The AI tool ChatGPT was used in the process of translating this study into English.

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Chapter 8- Artificial Intelligence Applications in Human Resource Management

Abdullah Yiğit Güngör

Chapter Highlights

- The chapter explores the applications of artificial intelligence (AI) in human resource management (HRM).
- The evolution of AI in HRM is outlined.
- Key examples of AI applications in HRM are given.
- The potential benefits and risks of AI applications in HRM are discussed.
- Practical guidance for the application of AI in HRM is provided.

Introduction

The market of artificial intelligence (AI) has been increasing all over the world. According to Statista, the AI market is worth $244 billion in 2025, with generative AI accounting for $63 billion of that. With this rapid growth, the AI market value is projected to reach $800 billion by 2030 (Vailshery, 2025). According to a study conducted by the University of Melbourne and Klynveld Peat Marwick Goerdeler (KPMG), 66% of people regularly use AI, and 83% of them find it useful (Gillespie et al., 2025). In addition to the individuals, enterprises also benefit from AI to a considerable extent.

Eurostat, the official statistical office of the European Union (EU), states that around one in five enterprises used AI technologies in 2025. When it comes to large enterprises, the ratio rises from one in five to one in two enterprises in the EU. Scandinavian members (Denmark, Finland, and Sweden) are the leaders of AI use in enterprise, consecutively. In this context, the ratio is around 42% for Denmark, 38% for Finland, and 35% for Sweden. On the contrary, Romania (5%), Türkiye (7%), and Poland (8%) have the lowest ratio of AI use in 2025. The most commonly used AI types are text mining, generation of pictures/videos/audio, natural language generation and speech synthesis, speech recognition, automating various workflows, or assisting in decision making, respectively (Eurostat, 2025).

Types of AI show that the field of human resource management (HRM) can benefit significantly from AI. According to the report from McKinsey & Company (2025), around 50% of human resources (HR) employees indicated that the use of AI decreased the cost within the department. Similarly, the majority of participants revealed that the number of employees was cut down last year within the HR department, and this decline is expected to continue. Under these circumstances, both managers and employees working within the HR department should expand their knowledge regarding the use of AI in HRM. Hence, on one hand, decision makers will be able to enhance efficiency via AI; on the other hand, employees will update their knowledge, skills, and competencies to benefit from AI. Thus, it is crucial to comprehend the use of AI in the field of HRM.

Conceptual Framework

Artificial Intelligence

The concept of artificial intelligence (AI) dates back to the Dartmouth Conference held in 1956. Although a considerable amount of time has passed since the concept emerged, there are different perspectives on its definition. In this context, AI definitions have been classified under three headings. Accordingly, AI can be defined as a technology, a capability, or an intelligent action. As a technology, AI is a machine, technology, or software that enables computers to perform tasks requiring human intelligence. As an ability, AI is the ability of machines, computers, and systems to simulate, interpret, and learn human thought. As an intelligent action, AI refers to any kind of activity performed intelligently. Considering these definitions, AI as a capability can be seen as an extension of AI as a technology, while AI as an intelligent action can also be considered an extension of AI as a capability (Zhai et al., 2024).

In addition to academic definitions, the concept of AI has also been defined by leading dictionaries. In this context, AI is defined as computer technology that enables anything to be done in a manner similar to how it would be done by a human (Cambridge); the ability of computer systems or algorithms to mimic intelligent human behavior (Merriam-Webster); the capacity of computers or other machines to exhibit or simulate intelligent behavior (Oxford); the ability of a computer, computer-controlled robot, or programmable device to perform functions such as perception, learning, reasoning, decision-making, problem-solving, communication, etc., in a manner similar to humans (Turkish Language Association).

AI has significantly transformed the world from its early beginnings in the mid-20th century to the present day. This transformation has occurred through various technologies, purposes (e.g., face or image recognition), functions (e.g., language understanding or problem solving), and types of tools (e.g., robots, driverless cars). It also encompasses various methods and disciplines such as vision, speech recognition, and robotics. These developments show that AI supports the Sustainable Development Goals (SDGs) to a large extent (approximately 80%). For example, notable progress can be seen in areas such as diagnosis and predictive analysis in healthcare through AI (SDG 3); crop monitoring and climate resilience in agriculture (SDGs 2 and 15); personalized learning in education (SDG 4); and crisis mapping and aid distribution for humanitarian assistance (United Nations).

Human Resource Management

The concept of human resource management (HRM) emerged in the 1980s. However, it is known that some activities within the scope of HRM date back to ancient armies. This is because, even in those days, there was a need for activities such as the selection and training of army members. In this context, it can be seen that HRM activities date back to ancient times, but the conceptual emergence of the term took time (Dessler, 2016). However, throughout history, different expectations regarding HRM have emerged due to the impact of environmental changes. As a result of these expectations, various concepts have been used chronologically as follows: Manpower Management → Personnel Management → Human Resources Management → Intellectual Capital Management → Talent Management. At the beginning of this process, “people” were considered muscle power and seen as a significant cost factor, but today they are seen as a value that provides businesses with a competitive advantage through their innovative and creative characteristics. The elements that create this value can be expressed as the skills, talents, competencies, personality, and experience that people possess (Benligiray, 2016).

Various definitions of the HRM concept have been provided in different sources. In this context, HRM is defined as: the management of work and people to achieve desired results (Boxall et al., 2007); a strategic, integrated, and consistent approach to the employment, development, and well-being of people working in organizations (Armstrong, 2014); the process of addressing concerns related to employee recruitment, training, evaluation, and compensation, as well as working relationships, health, safety, and equality (Dessler, 2016); and designing formal systems within an organization to manage human talent in order to achieve organizational goals (Mathis et al., 2019).

Human resource management has various functions. These functions can be classified under four headings: acquisition, development, retention (of qualified personnel), and performance enhancement. The main areas of activity covered by these functions are as follows (Benligiray, 2016).

- **Acquisition of human resources:** planning human resources, analyzing and defining jobs, designing jobs, finding and selecting human resources, placing and training employees, promoting and transferring employees.
- **Development of human resources:** training, rewarding, career planning and development, and providing feedback.
- **Retention of qualified human resources:** compensation, increasing organizational commitment, protecting worker health and safety, maintaining industrial relations, and organizing cultural and social events.
- **Improvement of human resource performance:** performance appraisal, disciplining, and evaluating HRM results.

Application of AI in HRM

To examine the applications of AI in HRM, it is necessary to understand the historical development of this process. In this context, four milestones can be identified. These are the info renaissance period (1990-2009), the data revolution period (2010-2018), the tech fusion epoch period (2019-2023), and the intelligence era (2024-present). During these periods, the role of artificial intelligence has evolved into expert systems, data analytical tools, augmentation platforms, and competitive resources. In this context, artificial intelligence is still a critical competitive advantage factor for HRM today. The evolution of artificial intelligence applications in the field of HRM is shown in Table 1 (Gong et al., 2025).

Table 1. Evolution of AI applications in HRM

Period	Role of AI	HRM Applications
1990-2009: Info renaissance	Expert systems	Expert systems were used for the selection of candidates and arrangements of shifts.
2010-2018: Data revolution	Data analytical tools	Human resources information systems were developed for employee monitoring.
2019-2023: Tech fusion epoch	Augmentation platforms	AI and robotics reshaped the global HRM (such as remote work)
2024-present: Intelligence era	Competitive resources	AI can promote sustainable HRM (e.g., ethical risk detection).

Source: Adapted from Gong et al. (2025)

There are various studies on the application of AI within the scope of HRM (e.g., Aguinis et al., 2024; Chowdhury et al., 2023; Johnson et al., 2022). Zhai et al. (2024) can also be considered one of the significant studies in this field. According to the study, human resources planning, recruitment and disposition, training and development,

performance evaluation, composition, and labor relations are the areas of HRM where AI is applied. Table 2 lists these areas and the AI techniques and applications used.

Table 2. Application Fields of AI in HRM

AI Application Field	AI Techniques and Applications
Human resource planning	*Evaluation of alternatives:* Artificial neural networks, cognitive computing, fuzzy theory, genetic algorithms, multiagents, and probabilistic reasoning can be used (Phillips-Wren et al., 2009).
Recruitment and disposition	*Diversity recruitment:* Bayesian models of variable order can be implemented (Pessach et al., 2020).
Training and development	*Training:* E-learning, which is a web-based teaching method, can be used (Orvis et al., 2011).
Performance	*Performance feedback:* Computerized performance monitoring can be used (Earley, 1988).
Composition	*Salary:* Machine learning can be used to estimate the contract salary of the candidate (Lin et al., 2016) and develop compensation models (Zhou, 2016).
Labor relations	*Employee turnover rate:* Logistic regression can be used to calculate (Stoltzfus, 2011).

Source: Zhai et al. (2024)

Chowdhury et al. (2023) provided examples of applications for HRM functions in their study. The HRM functions covered in this context include job application, candidate recruitment, onboarding, employee engagement, career development, performance appraisal, compensation, employee development, employee attrition detection, workforce management analytics, HR budget, and resource allocation. In this vein, AI technologies such as digital virtual assistants (chatbots) supported by automation, big data analytics, or data mining, can be used in a particular HRM function.

- **Job application:** Inquiries of candidates are handled via digital virtual assistants (chatbots) simultaneously. Hence, the e-mail workload of HRM is mitigated; evaluation of the curriculum vitae of the candidates is carried out, and preselection is completed. Additionally, feedback is given to the eliminated candidates and remained. In this way, objectivity and transparency of the selection process are provided (van Esch et al., 2021; Upadhyay & Khandelwal, 2018).
- **Candidate recruitment:** During the job interview, question reccommendations and performance appraisal are obtained via AI, which is integrated with video scanning and machine learning assistance. The likelihood of a job offer being accepted can be estimated. Moreover, future performance and expected working period of the candidate can be foreseen (van Esch et al., 2019; Upadhyay & Khandelwal, 2018).
- **Onboarding:** The orientation process is supported through digital virtual assistants. For this purpose, digital virtual assistants answer the questions of newcomers, direct them regarding the tasks, remind the duties, helping them to learn adequately (Babic et al., 2021).

- **Employee engagement:** Shifts and meetings are automated and personalized. Timely suggestions or warnings are provided to support decision-making. Collaboration is promoted by gathering employees who have similar profiles. Suitable mentors are appointed to the particular employees (Wang et al., 2021).
- **Career development:** Career goals of employees are elicited. Accordingly, career pathways are constituted, which include personalized skill, training, and development requirements. Additionally, employees are motivated for performance enhancement through competence maps (Braganza et al., 2021).
- **Performance appraisal:** Employee performance is estimated before the evaluation stage. During the evaluation, current and expected performance are compared. Suggestions are made for both managers and subordinates according to this difference. Hereunder, employees might be awarded through bonuses or promotion (Krekel et al., 2019; Smith, 2019).
- **Compensation:** A salary system is established with data-driven calculations. This smart system considers several indicators such as performance trends, productivity, significance level, and so on. Additionally, external data can also be used through comparison of the employees with competitors (Zehir et al., 2020).
- **Employee development:** An automatic skill map is generated, which justifies the need for training and organizes it. This smart way also provides a monitoring opportunity for HR regarding the whole learning process of employees. Hence, this process is audited by the managers. Furthermore, required feedback is given to the employees whether they are on the right path or not (Bughin et al., 2018; Jaiswal et al., 2021).
- **Employee attrition detection:** Data obtained from previous experiences is used to predict the intention to leave. Machine learning models are useful to implement this process. Thus, factors related to leave are determined, required measures are taken, and employee turnover rate is controlled (Sabbineni, 2020; Shankar et al., 2018).
- **Workforce management analytics:** Problems regarding well-being, presenteeism/abstenteeism, or mental health are identified by gathering information from behavior, practices, or social media posts within any level of organization (individual/group/department). Hence, due precautions are taken and required improvements are made (Margherita, 2021).
- **HR budget and resource allocation:** All kinds of information collected from both internal and external environments are processed in consideration of the priorities of the organization. Thus, effective resource allocation alternatives are offered to the decision makers (Ahmed, 2018; Tambe et al., 2019).

The application of AI in the field of HRM results in various benefits for businesses. In this context, according to the study by Johnson et al. (2022), the potential benefits expected from the application of AI technology in HRM functions (talent acquisition, employee development, performance management, compensation, turnover, and retention) are as shown in Table 3. Thus, decision makers from the department of human resources can take the necessary actions by considering the benefits and the current status of their departments.

Table 3. AI and HRM

HR Function	Potential Benefit of AI
Talent acquisition	Expanding the candidate pool, increasing processing capacity, and improving the evaluation process
Employee development	Developing timely and personalized orientation/training programs
Performance management	Comparative and balanced performance evaluation system
Compensation	Automatic tracking of pay across multiple data sources
Turnover and retention	Anticipating potential resignations and creating strategic incentives

Source: Johnson et al. (2022)

There are two main types of classification used for AI. One categorizes AI based on its capabilities. According to this, there are narrow AI, general AI, and super AI types (Strelkova, 2017). The other classification considers the philosophy, purpose, and techniques used behind AI. Accordingly, there are limited memory, reactive machines, self-awareness, and theory of mind AI types (Chung et al., 2022). In this context, generative AI (e.g., ChatGPT, Gemini, Copilot), a type of narrow AI with limited memory, is the most commonly used type of AI.

On the one hand, generative AI (GenAI) is used in the field of HRM and provides many benefits. On the other hand, this use also carries certain risks. In this regard, Jiang et al. (2024) investigated the risks that may arise when genAI is applied in HRM. Within the scope of the study, risks were evaluated in terms of both impact level and likelihood of occurrence. According to the results obtained, high, medium, and low-level risks are as follows. Accordingly, it would be beneficial for HRM to conduct possible risk analyses and take necessary precautions.

- **High-level risks:** These are risk types with relatively high impact levels and likelihood of occurrence. Privacy and cyber security, ethical concerns, and trust are examples of such risks. Attacks manipulating GenAI results related to HRM or privacy breaches, the possibility of GenAI reinforcing biases through fabricated content, and excessive trust in GenAI can be cited as examples.
- **Medium-level risks:** These are risk types that either have a high impact level and low probability of occurrence, or a low impact level and high probability of occurrence. Employee well-being, verification process, barriers to innovation, job security, business model disruption, governance, resistance to change, task transparency, technology dependency, and workforce transformation are such risks. Employees' fear of losing their jobs due to AI, their resistance to change, and their increased stress levels can be given as examples.
- **Low-level risks:** These are risk types where either the impact level is average and the likelihood of occurrence is low, or the impact level is low and the likelihood of occurrence is average. Employee engagement, system integration, task complexity, job redefinition, resource constraint, upskilling, professional development, technical constraint, task automation, and communication pattern change are examples of such risks. As a result of routine tasks being performed by AI, HRM employees may become inadequate in terms of development, competence, and performance in the long term, and AI tools may require regular maintenance and updating.

GenAI is used extensively in both daily life and work. However, its effective usage rate is a subject of debate. Therefore, Auginis et al. (2024) have created a valuable guide for using GenAI in HRM. This guide aims to provide high-quality and effective prompts that can be used in HRM functions (recruitment and selection, compensation management, performance management, benefits management, professional development and training, strategic HRM, job analysis, and retention and separation). The relevant guide and the steps to follow are as follows.

1. **Clarification of HRM issue:** Indicate the specific field of HRM, such as selection, training, compensation, or performance evaluation, for the inquiry. Specify the problem or question.
2. **Provision of organizational context:** Give details about the industry, region, or scale of the business. Remark human capital characteristics, such as diversity.
3. **Use of uniform HRM terminology:** Utilise standard concepts or terms of HRM to prevent ambiguity.
4. **Specification of the desired result:** Elucidate the expected outcome or sought suggestion.
5. **Request for evidence-based suggestions (if necessary):** Ask for citations, research, case studies, analysis, or instances.
6. **Compliance with recognized best practices:** Follow established practices to reduce possible corrections, which are time-consuming and costly.
7. **Ensuring confidentiality:** Refrain from sharing any private information about the organization or employees. For this purpose, use anonymous scenarios.
8. **Continuity of communication:** Provide follow-up questions or feedback for any additional information. Adopt an interactive approach through identification.

Conclusion

This chapter covers the applications of AI in the field of HRM. For this purpose, it first presents striking statistics showing how rapidly AI usage is increasing worldwide, both individually and organizationally. From an organizational perspective, one of the most important departments affected by the use of AI is HR. For this reason, the historical evolution of AI applications in the HR field has been discussed, and important milestones have been highlighted. Subsequently, AI techniques and sample AI applications for HR functions are provided, along with their benefits. On the other hand, the different levels of risk associated with AI have been identified. Lastly, this chapter is completed with a practical guide developed for the use of generative AI. Eventually, a conceptual perspective is introduced in this chapter regarding the AI applications in HRM. In this direction, it is expected to shed light on both practitioners (HR managers, HR professionals, AI engineers, AI specialists), researchers, trainers, and policymakers. Future empirical studies will build upon this perspective to further deepen the existing knowledge in the field.

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Chapter 9- Artificial Intelligence Applications in Marketing and Sustainability

Rafet Beyaz

Chapter Highlights

- It Artificial intelligence (AI) is widely used across various marketing domains, offering numerous benefits and advantages.
- AI applications enable more effective, responsible, and sustainable marketing practices aligned with environmental, social, and economic objectives.
- AI enhances visibility and access to sustainable products, facilitates personalized pricing strategies, and improves resource efficiency in marketing activities.
- AI supports data-driven decision-making, enabling faster and more informed strategic choices that prioritize sustainability.
- The integration of AI with sustainable marketing approaches, such as green marketing and social marketing, contributes to long-term value creation.
- Ethical considerations, such as data privacy, transparency, and human-centeredness, are crucial in the responsible use of AI in marketing.
- Future research should empirically examine the long-term effects of AI on sustainable consumption behaviors across different contexts.

Introduction

Throughout history, various developments in social life have led to the emergence of new economic conditions. In this context, the new economic conditions, which are based on the digital revolution and the management of information, have given rise to new marketing environments. This period, often referred to as the Information Age, has resulted in highly competitive markets. Before addressing the new economic conditions and the marketing phenomena they have generated, it is essential to examine how society and industry have transformed over time and how contemporary production processes have been established (Eser, Korkmaz, & Öztürk, 2022, pp. 41–42).

Diachronically, technology has been one of the primary elements that transform human life and support cultural development. In this context, all events throughout human history—from prehistoric times to contemporary societies—should be evaluated in accordance with discoveries in tool technology. Within this framework, technological advancement has been a fundamental factor in nearly all areas of societal development, from the natural lifestyle of hunter-gatherer societies, referred to as Society 1.0, to the present-day Society 5.0, in which humanized robots coexist with humans and share life experiences through devices based on augmented reality. In this process, technology has significantly influenced a wide array of cultural aspects, including nutrition, shelter, clothing, kinship relations, narrative traditions, music, entertainment and dance arts, belief systems, as well as marriage and birth rituals (Koçak, 2020).

As illustrated in Figure 1, humanity relied on hunting and gathering until approximately 13,000 BCE. This societal structure is referred to as “Society 1.0.” From this period onward, societies transitioned to the “Agricultural Society (Society 2.0)” by developing irrigation capabilities, then to the “Industrial Society (Society 3.0)” through the invention of steam engines enabling mass production, and later to the “Information Society (Society 4.0)” with the invention of the computer by the late 20th century. Finally, by learning to produce knowledge through intelligent machines and tools such as artificial intelligence, humanity has entered the “Smart Society (Society 5.0).” As observed, technological innovations have been the primary driver behind all societal transformations (Yıldız, 2018).

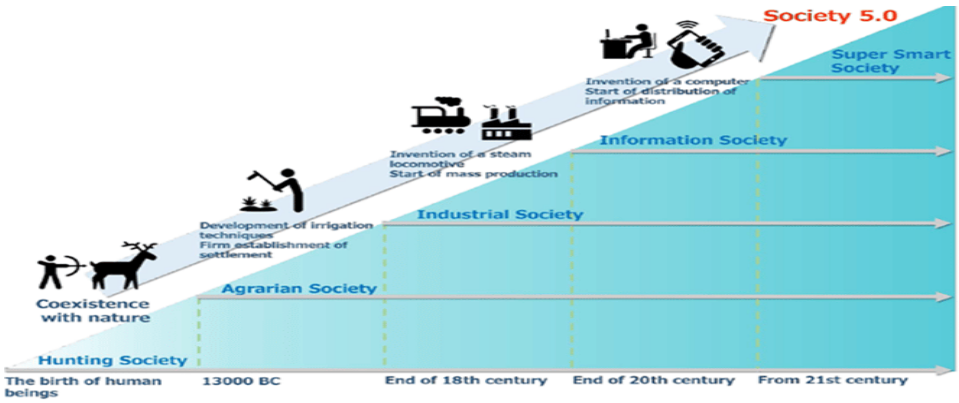

Figure 1: The Evolutionary Process of the Society 5.0 Concept

Source: (Fukuyama, 2018)

First officially proposed in Japan in 2016 through the Cabinet's approval of the 5th Science and Technology Basic Plan, the concept of Society 5.0 (S5.0) aims primarily at integrating technological advancements into society. Due to its focus on harmonizing society with technology, it was designated as Society 5.0 rather than Industry 5.0. Unlike previous revolutions, Society 5.0 emphasizes human, environmental, and social considerations, organizing itself around sustainable development goals and fostering a more democratic and inclusive framework. Earlier revolutions predominantly focused on increasing production, enhancing efficiency, and maximizing profit, often resulting in the neglect of natural resources and environmental limits. Recent developments—particularly following the COVID-19 pandemic—have highlighted challenges such as insufficient healthcare resources, the increasing frequency of natural disasters due to climate change, and economic difficulties arising from resource scarcity. This context underscores that a purely efficiency- and profitability-oriented approach is insufficient, emphasizing the importance of aiming for a more livable world. To achieve this goal, the transition to super-smart societies within the framework of Society 5.0, which is based on human-robot collaboration, has been emphasized (Duman, 2022, pp. 313–314).

The concept of Society 5.0 emerges as a solution to the challenges of optimized production and work distribution within the framework of Industry 5.0. It represents a futuristic vision that integrates digital transformation with societal needs. Society 5.0 is not merely a technological advancement; it constitutes a vision for a new social model. The concept emphasizes the use of advanced technologies such as artificial intelligence, the Internet of Things, and big data to address societal challenges, thereby transcending the traditional boundaries of Industry 4.0. While Society 5.0 embodies a broader societal vision, Industry 5.0 remains primarily focused on industrial aspects (Bakator, Cockalo, Makitan, Stanisavljev, & Nikolic, 2024:1).

There is a significant intersection between Society 5.0 and Industry 5.0. Both visions are complementary and advocate for the human-centered integration of advanced technologies. While Society 5.0 provides a comprehensive framework for societal transformation, Industry 5.0 outlines a roadmap for industrial evolution within this context. Industry 5.0 brings changes not only in production but also across other sectors such as transportation and logistics, marketing, and communication. Building upon the broader concept of Industry 5.0, Marketing 5.0 aims to maintain competitiveness and sustainability within Society 5.0. These three concepts constitute the foundational pillars of modern social, political, and economic dynamics (Bakator et al., 2024:1–2). By definition, Marketing 5.0 is understood as "*the use of applications that emulate human behavior to create, communicate, deliver, and reinforce value throughout the customer journey*." One of the most critical aspects of Marketing 5.0 is the deployment of a range of technologies designed to imitate the skills of human marketers. Technologies such as artificial intelligence, natural language processing, robotics, augmented reality, virtual reality, the Internet of Things, and blockchain are among the tools employed in this context. Marketing 5.0 emerges as a combination of these advanced technologies (Kotler, Kartajaya, & Setiawan, 2022, pp. 18–19).

As in all other domains, this process has brought significant changes to market and marketing conditions. The new economic environment, shaped by intensive use of information, has created highly competitive markets, while globalization and digitalization have fundamentally transformed information utilization and economic landscapes. With the widespread adoption of the internet and free trade, global competition has emerged. Whereas

businesses in the past targeted markets on a mass scale, contemporary firms assess all possible options individually in order to define their target markets. Similarly, while earlier enterprises produced products with long life cycles, today, every product and service is continuously and rapidly updated to meet the desires and expectations of consumers (Eser, Korkmaz, & Öztürk, 2022, p. 43).

In this approach, technological advancements and rapid transformation focus not only on economic growth and efficiency gains but also on achieving societal objectives such as reducing social inequalities, supporting the elderly, and addressing environmental issues. The intersection of Society 5.0 and sustainable marketing represents a significant turning point in terms of ethical responsibility, advanced technologies, and human-centered innovation. In this context, marketing has evolved beyond merely producing persuasive messages or promoting products to become a strategic function capable of creating system-level change. The use of digital technologies to support sustainability, equity, and collective well-being is considered a fundamental driver of this transformation (Bilge Turna & Karabel, 2025).

Within the scope of this study, the concept of Marketing 5.0 will first be examined. Subsequently, in connection with the Marketing 5.0 phenomenon, Artificial Intelligence (AI) Marketing—considered part of the marketing of the future—and its relationship with sustainability will be analyzed.

Artificial Intelligence and Marketing Applications

Although often perceived as a recent concept, the origins of artificial intelligence (AI) date back several decades. The term was first introduced in 1956 during the "Dartmouth Conference," proposed by a group of distinguished computer scientists and mathematicians (Hildebrand, 2019, p. 11). AI has been defined in more than seventy different ways by psychologists, sociologists, biologists, neuroscientists, and philosophers, making it a complex and difficult-to-define concept. However, the literature also presents definitions with considerable inclusiveness (Gür, 2022, p. 134). AI is generally regarded as the capability of computer systems to reason, learn, and act in a manner similar to humans (Russell & Norvig, 2022). In this context, AI—commonly defined as "intelligence exhibited by machines" (Siau, 2017)—is characterized by the ability to accurately interpret external data, learn from these data, and achieve specific goals and tasks through flexible adaptation based on such learning (Kaplan & Haenlein, 2019, p. 15).

AI applications significantly impact numerous sectors, including education, healthcare, manufacturing, marketing, law, and e-commerce. These tools have become an integral part of daily human activities, serving as assistants that facilitate everyday life. For instance, users can leverage automated email filtering to implement more efficient communication models. Additionally, individuals can utilize smartphones equipped with AI assistants (such as Siri, Cortana, or Bixby) to create calendars, receive support during driving, automate business processes, generate insights from historical data, and produce consumer and market insights through program-based algorithms (Verma, Sharma, & Maitra, 2021).

Chapter 9: Artificial Intelligence Applications in Marketing and Sustainability

From a sectoral perspective, marketing is one of the areas with the highest adoption of artificial intelligence (AI). AI applications are evident across numerous marketing domains. For instance, Amazon.com's Prime Air system, which automates shipping and delivery using drones, exemplifies such use. Similarly, Domino's Pizza has experimented with autonomous vehicles and delivery robots to deliver pizzas to customers' doors; RedBalloon utilizes the Albert AI marketing platform to discover and reach new customers; Macy's On Call employs natural language processing to provide customers with a personal in-store assistant; Affectiva recognizes consumers' emotions while they watch advertisements based on emotional analytics; and Replika, a machine learning–based chatbot, mimics consumers' communication styles to provide emotional comfort (as cited in Gür, 2022, p. 138). Research indicates that AI is applied across nearly all areas of marketing. In his study, Kamran (2021), drawing on the work of Campbell, Sands, Ferraro, Tsao, and Mavrommatis (2020), presented a table outlining the domains in which AI is utilized within marketing.

Table 1: The Use of Artificial Intelligence in Marketing

Areas of Application	Examples of Use
● Exploration of socio-cultural trends; ● Stock market and more advanced macroeconomic forecasts.	Social Media and Online Forums
● Identifying customer thoughts, sensitivities (body language and sentiment analysis), and market opportunities; ● Monitoring competitors.	Under Armour, Medallia, Rosbank, Neurodata Labs
● Individual segmentation; Clustering and targeting optimization of consumers based on extensive data.	Albert and Harley-Davidson, IBM SlamTracker and Wimbledon
● Estimating product sales, revenue, and expenses; ● Digital Customer Service (chatbot); ● Estimating consumer sentiment; ● Identifying customers most likely to make a purchase.	Aviso, Data-Robot, Amazon Sager-Maker ve Expedia, Starbucks Barista Bot,
● Developing new products based on trends; ● Creating highly personalized products; ● Selecting products that are worth producing and selling.	Choosy Fast Fashion, Zozo, Lily APP, Levi's, Samsung and Crimson Hexagon
● Estimating consumer price elasticity; ● Dynamic pricing and price discrimination; ● Detecting anomalies.	Wise Athena, Amazon, Airbnb
● Distribution and inventory management and optimization; ● Recommendation systems; ● Enabling voice and visual search; ● Optimizing store layout and design; ● Creating new channels.	Afesh, Celect, Reflektion, IMAGR, GrokStyle, COSMOS, Browzzin, Pinterest, Walmart
● Creating, placing, retargeting, and optimizing customized content, ads, and promotions; ● A/B testing.	Watson Ads Omni, Lego, Viscovery, 20th Century Fox and IBM Watson, NBA and WSC Sports

Source: (Kamran, 2021: 44)

As shown in Table 1, artificial intelligence is utilized across nearly all marketing activities, including the formulation of marketing strategies, market and customer analyses, situational analysis, marketing mix strategies, supply chain management, marketing communications, and the creation and delivery of digital services. In this study, the areas in which AI is applied within marketing activities will be presented under various subheadings.

The Use of Artificial Intelligence in Marketing Strategy and Planning Activities

With the increasing adoption of artificial intelligence, businesses are able to collect data using various tools, process the gathered data, and transform it into actionable insights through algorithms, thereby enabling the delivery of personalized customer services (Wellers et al., 2017).

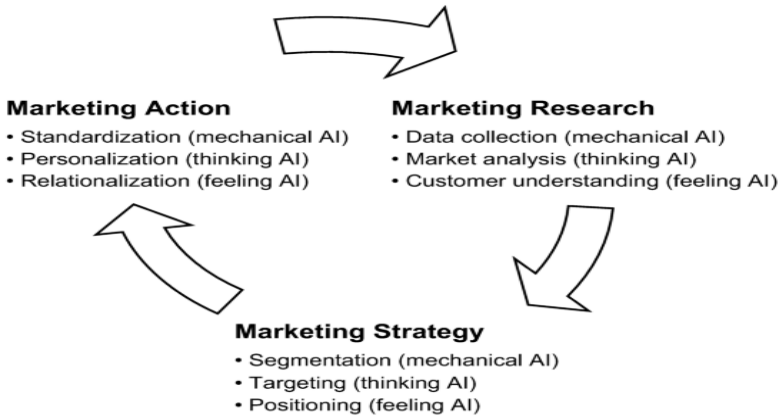

Figure 2. Marketing Strategy and Artificial Intelligence

Source: (Huang and Rust, 2021).

As illustrated in Figure 2, artificial intelligence plays a critical role in a circular process that ranges from conducting marketing research to understand the market, the firm, competitors, and customers, to developing segmentation, targeting, and positioning strategies, and designing specific marketing actions to execute the strategy. Therefore, a marketer must leverage multiple forms of AI, such as "mechanical, thinking, and feeling" AI. In this regard, AI can be defined as the use of computational machines to imitate human-specific abilities, including performing physical or mechanical tasks, thinking, and feeling. Multi-AI, on the other hand, refers to designing AI not merely as a thinking machine but as possessing multiple intelligences for different tasks, similar to human capabilities (Huang & Rust, 2021, pp. 31–32).

The Use of Artificial Intelligence in Product Management

The production function encompasses the transformation of raw materials into products or services and includes processes such as production planning, resource management, and quality control. Its primary objective is to manufacture goods or deliver services in a timely and cost-effective manner that meets customer demands. Effective production management enhances efficiency, increases a firm's competitiveness, and improves its capacity to respond quickly to market demands. Artificial intelligence plays a significant role in the automation

of production processes. AI systems such as robotic process automation (RPA) and machine learning enhance productivity by executing routine tasks more quickly and accurately, allowing employees to focus on strategic responsibilities. Furthermore, AI is critical in the maintenance and repair of production equipment. AI-driven predictive maintenance systems continuously monitor equipment performance data to detect potential failures in advance, identify areas requiring maintenance, and provide early intervention strategies that reduce unplanned downtime and associated costs (Uçar & Bulut, 2024).

Artificial intelligence is regarded as a crucial tool that can be widely applied across all stages of the product life cycle. Product life cycle management involves numerous engineering, business, and managerial activities throughout the entire lifecycle of a product, from the initiation of the production process to the disposal of the finished product. The emergence and rapid advancement of information technologies such as cloud computing, the Internet of Things, big data, and artificial intelligence are transforming the advanced manufacturing paradigm, affecting all aspects of product life cycle management. AI technology supports product design in two main ways. AI algorithms can utilize data mining during the product life cycle management process to analyze market trends and assist designers in achieving rapid and personalized product designs (Wang, Liu, Liu, & Tao, 2021).

Moreover, artificial intelligence can be applied in areas such as material procurement, resource allocation, production planning, processing, assembly, quality control, storage, and logistics. AI contributes to the improvement of the product manufacturing phase in two main ways: by optimizing the production management process through AI algorithms and by substituting human labor with AI-enabled devices. Additionally, the integration of AI with production systems facilitates significant advancements in human–machine collaboration, fault prediction, intelligent decision-making, and other related areas (Wang, Liu, Liu, & Tao, 2021).

The Use of Artificial Intelligence in Pricing Strategies

Although numerous factors influence consumer purchasing behavior, price is undoubtedly one of the most significant. As one of the elements of the marketing mix, price encompasses economic, psychological, and various subjective factors, including all material and immaterial costs incurred, and is therefore considered a crucial determinant. How price is perceived by consumers and its impact on the purchasing process provides marketers with substantial advantages. Improper implementation of pricing policies can lead to various issues, such as loss of market share and reduced profitability (Leblebicioğlu & Bilgen, 2019).

While pricing is highly important for business profitability, it is also a complex and challenging concept to implement. Changing time and demand conditions necessitate real-time price adjustments, complicating pricing strategies. AI applications are known to play a significant role in addressing this complexity. In this context, AI tools are used to dynamically adjust real-time pricing strategies for products and services. Particularly on e-commerce platforms, continuously changing pricing policies can pose challenges for sellers. AI tools, through machine learning, can continuously monitor competitors' pricing strategies and enable rapid price adjustments. Moreover, AI algorithms can be employed to consider customer choices, competitor strategy identification, and supply processes. In this process—also referred to as dynamic pricing—AI algorithms determine price levels

based on market dynamics such as product pricing, consumer behavior, and supply and demand conditions (Kuruca, Üstüner, & Şimşek, 2022, p. 99).

Historically, airlines are among the first firms to adopt artificial intelligence. These companies have leveraged AI to automate pricing decisions. Setting a price for a flight is subject to sudden daily fluctuations, making it inherently complex and dynamic due to the numerous influencing factors. Airlines experience rapid changes both in demand (customers' booking behaviors) and in capacity (seat availability). Research indicates that flight prices vary significantly day-to-day depending on factors such as the timing of purchase relative to departure, competition on a specific route, and the number of seats sold (Aparicio & Misra, 2023). AI algorithms designed to address this complex and rapidly changing environment enable firms to establish pricing strategies that respond swiftly to fluctuations in customer demand and competitive conditions.

Use of Artificial Intelligence in Distribution

In general terms, a distribution channel refers to the system that begins with the manufacturer and continues through wholesalers, retailers, and ultimately consumers. In other words, it encompasses all individuals and institutions involved in delivering products and services from production centers to end users (Öz, 2008: 1–2). These channels, which enhance the availability of products and services in the marketplace, constitute fundamental mechanisms that facilitate customer access to products and ensure customer satisfaction. The product distribution process involves highly complex relationships with numerous actors. Within this process, a wide range of activities—such as inventory management, logistics, transportation, and warehousing—are carried out to ensure that the right product is delivered to the right customer at the right time in an efficient and reliable manner. Firms that manage this process effectively contribute to customer satisfaction by offering low-cost products and, consequently, increase their market share (Bilginer, Kayabaşı, & Sezici, 2008).

The logistics sector, which has been gaining increasing importance both globally and in Türkiye, has begun to adopt new applications and tools in parallel with technological advancements. One of the most significant tools utilized in this context is artificial intelligence (AI) applications. AI is employed in a wide range of logistics activities, including customer churn prediction, demand forecasting, inventory management, procurement, vehicle routing, logistics operations planning, logistics tracking, order picking, quality control in the supply chain, equipment maintenance and repair, warehouse systems, and shipment operations (Aylak, Oral, & Yazıcı, 2021).

In this process, AI-based solutions are implemented through the use of collaborative robots (cobots) in packaging, drones in delivery, the Internet of Things (IoT) in order tracking and inventory management, and autonomous driverless vehicles in transportation. Moreover, in some factories—referred to as "dark factories"—production and distribution systems are operated entirely without human labor. For instance, major commercial enterprises such as Amazon Go and Alibaba maintain their production and distribution systems almost entirely through artificial intelligence applications (Kuruca et al., 2022, p. 99).

Artificial Intelligence Applications in Promotional Activities

In recent years, artificial intelligence has offered an automated and data-driven approach to various tasks that were traditionally performed manually. In this context, AI has emerged as a significant factor in the design, execution, and reconfiguration of promotional campaigns. Artificial intelligence provides a range of advantages for promotional activities through advanced automation, predictive analytics, and enhanced targeting and personalization capabilities. These advantages enable firms to improve their promotional campaigns and manage them more efficiently and effectively (Kivistö, 2024, p. 3).

Promotional activities within the marketing mix encompass media planning, the management of advertising campaigns, search engine optimization (SEO), and various digital communication practices. Today, marketing professionals make extensive use of artificial intelligence technologies to enhance the effectiveness of digital advertising processes. AI algorithms employed in activities such as measuring advertising performance, determining customer conversion rates, and analyzing user interactions continuously optimize advertising campaigns, thereby enabling the delivery of more relevant and targeted content to consumers. Through its advanced data analytics capabilities, artificial intelligence facilitates the delivery of customized products and services to customers and enables firms to develop more effective business models. In this way, it becomes possible to reach the right customers at the right time with appropriate campaigns. In the contemporary marketing environment, where digitalization is accelerating, the widespread adoption of social media and digital marketing practices has further increased the importance of AI-supported personalized campaigns. In this context, personalized promotional campaigns based on customer characteristics can be developed through the use of artificial intelligence technologies (Kuruca, 2022, p. 100).

In recent years, the intensive integration of digital technologies into daily life has led to a profound transformation in marketing practices. This transformation has particularly resulted in a marked increase in the use of artificial intelligence in promotional activities. The change has affected a wide range of areas, from brands' promotional strategies to the content production processes of social media marketing specialists. In this context, a published report indicates that social media professionals carry out 82% of their idea generation processes, 85% of their content copywriting activities, and 52% of their visual production processes through artificial intelligence tools. The same report also emphasizes that consumers experience considerable difficulty in distinguishing a significant portion of AI-generated content from human-produced content. The trends identified in this report, which was published in 2024, appear to have continued in subsequent years. As of 2025, it is stated that 83% of marketers utilize artificial intelligence tools in content production. Accordingly, it has been observed that a substantial number of brands include expressions such as "designed with artificial intelligence" or "we asked artificial intelligence" in their advertising content (Çil & Erkan, 2025). In summary, it can be argued that artificial intelligence tools are used extensively across almost all elements of the promotional mix in the product promotion process. In this regard, the areas of application of artificial intelligence tools in promotional activities are presented in Table 2 (Bieliaiev, 2025).

Table 2: AI use cases within the scope of promotional components

Promotion Component	Artificial Intelligence (AI) Use Cases
Advertising	1. Ad optimization. 2. Content creation. 3. Ad concept development. 4. Ad automation.
Public Relations	1. Media monitoring and sentiment analysis. 2. Target audience analysis. 3. Monitor competitor behavior. 4. Multilingual public relations campaigns. 5. Chatbots for interaction.
Personal Selling	1. Create personalized offers. 2. Skip irrelevant offers.
Sales Promotion	1. Dynamic pricing. 2. Personalized discounts and offers. 3. Loyalty program customization. 4. Geographically targeted promotions. 5. Sending reminders about pending orders.

Within the scope of marketing, artificial intelligence is also utilized across various domains, including customer relationship management, brand management, and the analysis of consumer behavior. Customer relationship management is a strategic management approach aimed at identifying the right customer segments, enhancing these customers' loyalty to the firm, and thereby maximizing profitability through the achievement of a sustainable competitive advantage. In this context, the concept of "selecting the right customer" refers to the clear and systematic definition of the customer group that the firm intends to serve. Analyzing the wants, needs, and expectations of the identified customer segments should be regarded as a fundamental input in product and service development processes. Through this approach, customer requirements can be addressed effectively, which in turn contributes to increased customer satisfaction (Ersöz, Yaman, Birgören, 2008).

The integration of artificial intelligence with CRM systems enables in-depth analysis of customer data, allowing for a more comprehensive understanding of customer behaviors and more accurate forecasting of future needs. Through this integration, firms can develop insights based on historical purchasing data and offer more personalized products and services; moreover, they can identify customer dissatisfaction in real time and intervene promptly, thereby strengthening customer relationships. In addition, AI-powered CRM applications facilitate the creation of customized campaigns by sales and marketing teams, enable more effective targeting of potential customers, and support more efficient management of sales opportunities. By automating business processes, these applications enhance operational efficiency and contribute to the development of a more data-driven and competitive organizational structure (Josiassen, Assaf & Cvelbar, 2014).

Artificial intelligence also plays a significant role in brands' creative processes. The use of AI technologies in the generation of visual and text-based content enables the development of creative and compelling materials that strengthen brand identity. By automating content production processes, artificial intelligence contributes to faster, more consistent, and more efficient content creation for brands. For instance, AI-based content generation tools are capable of producing various types of content, such as blog posts, articles, and social media posts. In addition, artificial intelligence supports brands in the creation of visual elements, including logos, websites, and other design components; AI-driven design tools offer creative ideas and recommendations to enhance brands' visual identities (Çakmak, 2024).

As observed, artificial intelligence is widely recognized as a technology that provides numerous benefits across many sectors and fields. In this context, it offers advantages such as 24/7 availability, reduction of human errors, increased accuracy and efficiency, and the ability to make decisions more rapidly and with lower risk. However, it also has certain disadvantages, including high implementation costs, a lack of creativity, the absence of emotional intelligence, and limited improvement through experiential learning. In this regard, it is evident that artificial intelligence applications used within the scope of marketing also involve various disadvantages. Some of these disadvantages are outlined as follows (Alkaddour, 2022, p. 59; dentsu.com).

- *Artificial intelligence can be used for fraudulent purposes*. It may facilitate the creation of fake accounts to manipulate perceptions, deceive individuals, and influence public opinion.
- *Uncertainties may arise in reliable prediction and analysis*. Artificial intelligence is known to face significant challenges, particularly in sentiment analysis (e.g., happiness, excitement, sadness, sarcasm).
- *Chatbots are not always preferred*. Users often favor interaction with human agents rather than robots, especially when dealing with complex issues.
- *The requirement for large volumes of data.* To obtain accurate and reliable outcomes, artificial intelligence systems require sufficient and high-quality data. In this regard, incomplete, inaccurate, biased, or insufficient data storage can lead to erroneous results. Moreover, firms must possess adequate technological infrastructure to support these processes.
- *Data privacy concerns.* Data privacy violations may harm corporate reputation and lead to significant legal sanctions.

The Relationship Between Sustainable Marketing and the Use of Artificial Intelligence

As a concept, sustainability has increasingly gained prominence in both academic literature and policy documents since the last quarter of the twentieth century, alongside the global rise in environmental degradation, the rapid depletion of natural resources, and growing social inequalities (Koçak, 2025, p. 110). Sustainability, defined as the capacity for continuity, refers to the necessity of harmonizing relationships across different domains. The concept is grounded in the principle that present needs should be met without compromising the ability of future generations to meet their own needs. In this context, while improving current economic conditions, efforts are made to ensure that the economic well-being of future generations is not adversely affected (Şen, Kaya, & Alpaslan, 2018).

The concept of sustainability is important not only for the improvement of environmental policies but also for ensuring long-term stability in economic and social domains (Koçak, 2025, p. 110). This perspective indicates that sustainability is structured around three main pillars—economic, social, and environmental. These components must be designed in a balanced and optimal manner in order to establish a sustainable development model.

The concept of sustainability is built upon four fundamental principles: precaution, participation, equity, and intergenerational equity. The principle of precaution refers to the development of foresighted, preventive, and cautious policies in the face of risks and uncertainties. The principle of participation emphasizes the inclusion of all stakeholders in decision-making processes and advocates for these processes to be conducted in an inclusive manner. The principle of equity highlights the fair and balanced distribution of resources and opportunities in meeting the needs of all segments of society. Finally, the principle of intergenerational equity aims to ensure that the well-being of future generations is taken into account in the formulation of current policies and practices, promoting a balanced approach between present and future needs (Demiroğlu & Ulusoy, 2024, p. 4).

The phenomenon of sustainability is regarded as a multidimensional concept with a broad field of application, addressed within the frameworks of different sectors and disciplines. The ability of this phenomenon to generate the desired outcomes and to be implemented effectively depends on the active contribution of all stakeholders involved in the process. In this context, one of the key disciplines in which sustainability has gained prominence is marketing. The sustainability-oriented approach adopted in the field of marketing has the potential to transform numerous sectors through its wide-ranging impacts. Consequently, the concept of sustainable marketing has been increasingly discussed in academic literature in recent years.

Although sustainable marketing is defined in various ways, Martin and Schouten (2014) describe it as the preservation and enhancement of human and natural capital in the process of creating and delivering value to customers (Tiğiz & Özsaatcı, 2024, p. 47). This perspective does not confine sustainable marketing solely to the promotion of environmentally friendly products; rather, it conceptualizes it as a holistic approach aimed at restructuring all marketing activities—from production to consumption, from distribution to after-sales services—in line with sustainability principles. Within this framework, firms assume responsibility not only for delivering value to consumers but also for developing solutions that emphasize environmental protection, prioritize social justice, and support economic sustainability. The growing sensitivity of contemporary consumers toward sustainability further reinforces firms' strategies and policies in this direction (Koçak, 2025, p. 111).

The concept of sustainable marketing is closely associated with Marketing 6.0. Marketing 6.0 represents a marketing vision in which sustainability-oriented strategies are integrated with AI-driven autonomous systems and blockchain technology. From the perspective of societal transformation, Marketing 6.0 has increased the emphasis placed on sustainability and ethical values. In this period, green marketing, social responsibility initiatives, and ethical branding practices have become decisive factors in shaping consumer loyalty. Consequently, this era is regarded as a holistic marketing approach that blends ethical digitalization, human-centered technologies, and sustainable development, with a strong focus on individual and cultural advancement.

Chapter 9: Artificial Intelligence Applications in Marketing and Sustainability

In contemporary marketing thinking, the creation of societal value, rather than a purely profit-oriented perspective, increasingly shapes marketing policies. Firms and brands seeking success in this environment are expected to use technology not solely to enhance efficiency, but also to contribute to building a healthy future for the planet as a whole (Alabay, 2025). Within the framework of the pursuit of sustainability, technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning, 5G communication, and cloud computing are widely employed for monitoring and improvement practices (Chaudhary, Gaur, & Rustagi, 2024).

AI-driven marketing applications enable marketing activities to be carried out in a more effective, responsible, and sustainable manner. Within this framework, the sustainable marketing approach emphasizes that marketing activities should be environmentally sustainable, socially equitable, and economically viable. Integrating sustainability into marketing strategies allows firms to strengthen their competitive advantage and align their organizational objectives with broader sustainability goals. This, in turn, fosters the creation of a mutually beneficial synergy for both businesses and society (Gündüzyeli, 2024).

A sustainable marketing approach that focuses on the creation of customer value, social value, and environmental value prioritizes long-term and enduring objectives over short-term gains. This perspective is grounded in the protection, development, and effective management of human and natural capital in the process of generating societal and customer value. In other words, sustainable marketing is guided by the principle of meeting consumers' wants and needs while preventing the emergence of social and environmental harm (Tiğiz & Özsaatcı, 2024). In recent years, various developments in the field of sustainability have paved the way for the increasingly widespread adoption of the sustainability paradigm within the marketing discipline (Cătoiu, Vrânceanu, & Filip, 2010).

- The formulation and enforcement of regulations related to environmental protection and environmental pollution,
- The increasing costs of inherently limited natural resources due to their finite nature,
- Changes in the attitudes and behaviors of consumers who have become more sensitive to sustainable solutions,
- The growing awareness of stakeholders regarding social responsibility initiatives,
- The increasing importance of developing sustainable strategies as a means of achieving competitive advantage have led firms to place greater emphasis on sustainable marketing practices.

Sustainable marketing possesses several distinctive characteristics. Some of these characteristics are expressed as follows (Tiğiz & Özsaatcı, 2024):

- *Environmental orientation:* This approach emphasizes increasing energy and water efficiency in the production of goods and services and reducing the amount of waste generated in order to minimize environmental harm.
- *Commitment to social responsibility:* In the process of providing goods and services, emphasis is placed on protecting and improving employees' rights, developing fair labor and fair wage policies, and enhancing overall working conditions in order to contribute to society.
- *Transparency*: Sustainable marketing is based on informing consumers about the social and environmental impacts of products and services.

- *A long-term perspective:* The primary objective is not to achieve high short-term profits, but to focus on sustainable and enduring gains in the long run.
- *Emphasis on stakeholder participation:* The sustainable marketing process encourages the active involvement of all stakeholders—particularly employees, customers, and civil society organizations—in contributing to the process.

When examined within the framework of environmental imperatives and the perspective of sustainable development, the application of artificial intelligence (AI) in marketing can be characterized as a "double-edged sword." On the one hand, AI systems used in marketing are largely oriented toward increasing sales and profitability; this focus may stimulate higher levels of consumption and, in turn, exacerbate environmental and social negative externalities. Moreover, the substantial energy consumption and carbon emissions associated with the development, training, implementation, and diffusion of AI technologies constitute a significant area of concern in terms of environmental impact. On the other hand, AI is also regarded as a powerful tool capable of supporting sustainability efforts on both the supply and demand sides. In this respect, the potential of AI to promote sustainability in marketing should be examined within the framework of the marketing mix—namely product, price, place, and promotion (the four Ps) (Hermann, 2023).

In this context, it is important to reassess production and consumption processes through a sustainability-oriented lens by taking into account green marketing, social marketing, and critical marketing approaches, which are widely recognized as the core dimensions of sustainable marketing. Green marketing emphasizes environmental responsibility through elements such as improving energy efficiency, reducing waste, using environmentally friendly packaging, and adopting self-sufficient production models. Social marketing, by contrast, aims to integrate economic, social, and environmental objectives within a holistic approach. The critical marketing approach adopts a questioning stance toward marketing from a sustainability perspective and foregrounds the concept of "demarketing," which advocates limiting consumption. This approach seeks to discourage consumers, in both the short and long term, from excessive and harmful consumption behaviors and aims to reduce the consumption of products and services that fail to generate benefits for society and the environment. Another key criticism raised by critical marketing concerns the tendency of marketing activities to focus exclusively on target markets, which may result in the neglect of individuals and social groups outside these defined segments (Soydan & Başkol, 2022). Within this framework, it is argued that the strategic steps to be taken can contribute to the development of sustainable solutions in the long run. The conscious and responsible integration of AI applications into this process is expected to enable more consistent and effective outcomes in achieving sustainable marketing objectives.

Artificial intelligence can guide product design and development processes by identifying the sustainability-related product and service attributes that consumers value most; moreover, through data derived from digital footprints, it contributes to the development of personalized pricing strategies based on consumers' willingness to pay for environmentally sustainable products. In addition, AI enhances the effectiveness of distribution and promotional activities by enabling the alignment of sustainable offerings with consumer segments that are psychologically more inclined toward such products and services.

However, these applications should not be designed solely around short-term sales objectives; rather, they should be structured in a way that encourages more informed and sustainable consumer decision-making and supports the principle of "better but less consumption" (Hermann, 2023).

The contributions that artificial intelligence can make within the scope of sustainable marketing manifest across multiple dimensions. These contributions can generally be examined under the headings of visibility and access, pricing, personalization, resource efficiency, and strategic decision-making (Cesur & Armutçu, 2023; Gündüzyeli, 2024; Zechiel et al., 2024; Hermann, 2023; Rathore, 2018).

First, AI-powered search engines, digital platforms, and websites enhance the visibility of sustainable products and services, facilitating consumer access to these offerings and supporting their wider adoption. By presenting consumers with sustainable alternatives, these systems contribute to the formation of more informed and conscious purchasing decisions.

One of the primary barriers to the diffusion of sustainable products—namely, the perception of high prices—can be mitigated through AI-driven pricing and comparison tools. These tools identify more affordable alternatives to environmentally friendly products across different retailers and present them to consumers, while simultaneously enabling the communication of their environmental benefits.

By facilitating the creation of personalized customer experiences, AI increases consumer engagement and loyalty and aligns marketing activities with individual preferences. In this way, firms can develop more targeted and effective strategies instead of resource-intensive mass marketing campaigns that lead to waste, thereby enhancing customer satisfaction while reducing resource consumption.

Moreover, AI improves the effectiveness of digital marketing through precise targeting and personalization, allowing marketing resources to be used more efficiently. The real-time analysis of large-scale data enables firms to make faster and more informed decisions, increasing operational efficiency while also contributing to the reduction of environmental footprints.
In addition, AI supports the development of innovative marketing strategies that prioritize sustainability. AI-driven insights help identify consumer preferences for environmentally friendly products and enable marketing campaigns to be adapted accordingly. This strategic alignment allows brands to gain a competitive advantage in the field of sustainability and to achieve long-term success.

Finally, by simultaneously analyzing consumer behavior and supply chain performance, AI enhances the accuracy of demand forecasting and contributes to the development of sustainable offerings and the reduction of waste. In doing so, firms can respond more rapidly to changing consumer expectations and implement environmentally friendly solutions more effectively.

Conclusion and Recommendations

This study examines the transformation taking place in the field of marketing through the lenses of Society 5.0, Marketing 5.0, and sustainability, and adopts a holistic perspective to analyze the effects of artificial intelligence (AI) applications on marketing processes. With the widespread diffusion of digitalization and advanced technologies, marketing has evolved beyond a function focused solely on sales and profitability to become a strategic activity that also encompasses social value creation, environmental responsibility, and long-term value generation. In this context, AI emerges as a transformative element in the planning, implementation, and evaluation of marketing activities.

The findings discussed in this study indicate that AI can be effectively utilized across all elements of the marketing mix—product, price, place, and promotion—while offering significant competitive advantages to firms. AI-enabled systems facilitate more accurate analysis of consumer needs in product development processes, the generation of dynamic and personalized solutions in pricing strategies, the optimization of resource utilization in distribution and logistics activities, and the development of more targeted and efficient communication strategies in promotional activities. In this regard, AI enhances operational efficiency, reduces costs, and increases the overall effectiveness of marketing efforts.

At the same time, the study draws attention to the dual nature of AI in the context of sustainable marketing. On the one hand, AI applications have the potential to intensify consumption and thereby increase environmental pressures; on the other hand, they constitute a powerful tool for enhancing the visibility of sustainable products and services, connecting consumers with environmentally friendly alternatives, and supporting more conscious consumption behaviors. Therefore, the use of AI in marketing should not be guided solely by short-term sales objectives, but rather be approached from a long-term strategic perspective that takes environmental, social, and economic sustainability into account.

The study also evaluates different dimensions of sustainable marketing within the frameworks of green marketing, social marketing, and critical marketing approaches, emphasizing the importance of integrating AI with these perspectives. Through AI-driven analytics, consumer attitudes and behaviors toward sustainable products can be better understood, and strategies that encourage sustainable consumption can be developed through segmentation based on psychological, socio-demographic, and behavioral data. However, throughout this process, it is critical not to overlook principles such as data privacy, ethical responsibility, transparency, and human-centeredness.

In conclusion, AI should be regarded not merely as a technological tool in the field of marketing, but as a strategic transformation element capable of contributing to sustainable development goals. Future research is recommended to empirically examine the long-term effects of AI-driven marketing applications on sustainable consumption behaviors and to conduct comparative analyses across different sectors and cultural contexts. Furthermore, collaboration among policymakers, academics, and practitioners in developing guiding principles for the ethical, responsible, and sustainable use of AI in marketing would generate lasting benefits for both businesses and society.

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Chapter 10- Artificial Intelligence in Financial Sytems

Mehmet Gözel

Chapter Highlights

- The chapter covers the applications of artificial intelligence (AI) in financial systems.
- The development of AI and the digital transformation of financial systems are utilized.
- The maturity status of AI in financial industries are outlined.
- The use of AI and explainable artificial intelligence (XAI) in financial issues is discussed.
- Practical guidance for the application of AI in finacial sytems are provided.

Introduction

Artificial intelligence (AI) is currently at the center of digitalization and technological developments. Although AI is perceived as a new technological tool, its origins date back to Alan Turing's question “Can machines think?” in the 1950s. This journey, which began with the belief that machines could think like humans, has continued to the present day with many developments and transformations. At this point, it is clear that AI has become integrated into our lives in every way and is now seen not just as a technological tool but as an economic and social dynamic. This is also valid for finance-the lifeblood of the economy, which relies on the opportunities offered by digitalization

Financial systems are mechanisms that include investors, savers, regulators, and supervisors. A system with so many actors undoubtedly requires technology and digitalization as a necessity of our time. At this point, AI tools, the cutting-edge technology of our era, come into play. Today, AI techniques such as deep learning, machine learning, and AI agents have found their place within financial systems and have provided convenience to businesses and individuals in many financial areas. AI's ability to think and solve problems like humans is notable for assisting users in various financial issues, including financial modeling, investment, savings, risk management, monitoring, valuation, forecasting, legal regulations, and e-commerce.

This chapter has been written to maximize the benefits that AI provides to financial science and to determine its position in financial systems. This chapter covers the development process of AI and its applications in financial systems, the maturity status of AI in the financial industry, and explainable artificial intelligence (XAI) methods in Finance.

Conceptual Framework

Definition and Development Process of Artificial Intelligence

Although there are different definitions, one of the most widely accepted definitions states that artificial intelligence (AI) is the study and design of intelligent agents that perceive their environment and act to achieve specific goals based on these perceptions (Russell & Norvig, 2010). The first steps related to AI were taken in the mid-20th century with the idea of machines being able to imitate human intelligence.

This process began with Alan Turing's (1950) question, *“Can machines think?”* and subsequently took on a measurable form with the “*Turing Test”*, demonstrating that a machine could perform indistinguishably from a human in written communication. The Turing Test brought to the forefront the idea that the mind can be explained through computational processes and laid the foundation for work on AI (Turing, 1950). Shortly thereafter, John McCarthy et al. (1955) introduced the term AI into the literature with their work titled “A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence.” With this work presented at the Dartmouth Conference, AI took shape as a field of research in which cognitive processes such as learning, reasoning, and problem solving could be modeled through machines.

AI researches in the 1970s and 1980s focused on expert systems. Expert systems aimed to automate decision-making processes by representing human expert knowledge in specific fields through rules. However, due to the costly knowledge acquisition process, inflexible structures, and scalability issues of these systems, financial and academic support for AI declined; this period is referred to in the literature as the first *"AI Winter."* Starting in the 1990s, a significant paradigm shift occurred in the field of AI, with statistical methods and probability models coming to the fore. By the 2000s, increased computing power and data volume enabled machine learning to become one of the fundamental components of AI, paving the way for the deep learning approaches that emerged after 2010 (Russell & Norvig, 2010).

From 2010 to the present day, thanks to the increase in big data and computing power, AI has begun to be widely used in business and daily life. During this period, AI-powered applications such as image recognition, smart assistants, and autonomous vehicles have become more common in daily life. This has paved the way for the public to use AI tools, especially as businesses have also begun to favor these tools. The key factor in this transformation is the development of artificial neural networks based on deep learning (Haenlein & Kaplan, 2019). The development process of AI is presented in Figure 1.

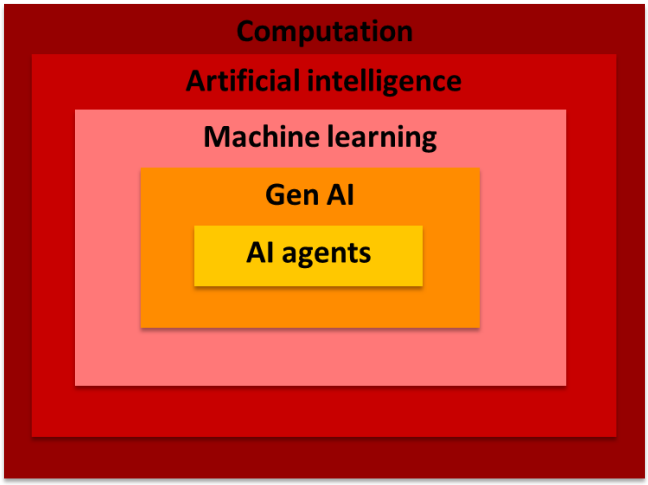

Figure 1. The Transformation Process of AI
Source: Aldasoro et al, 2024

At the current stage, thanks to the deep learning branch of AI, the ability to process large-scale data and solve complex problems has advanced and spread to financial systems. Therefore, it is important for financial system regulators and users to determine the areas of application for AI and to achieve high efficiency from it.

Digital Transformation of Financial Systems

All economic activities within the financial system, such as investment, risk, saving, and payment, have evolved over time. The Industrial Revolution, in particular, marked a turning point in terms of developments affecting the financial system, such as the increase in the number of joint-stock companies, the expansion of capital and money markets, and the laying of the foundations of modern banking. (Neal, 1990). In the 20th century, the role of central banks in economies strengthened, globalization in financial markets increased, and as a result, financial systems

expanded even further (Mishkin, 2022). This global economic stability and growth environment has contributed to the globalization of finance and the first steps towards digital transactions. Especially in the 1970s and 1980s, the proliferation of electronic trading platforms and automated systems paved the way for Financial Technology (FinTech) and created a digital environment for securities trading. With the emergence of online banking in the 1990s, the digitalization of financial systems accelerated significantly (Kamuangu, 2024).

In the 21st century, individuals and institutions are making faster decisions on financial matters, and the role of financial systems in this decision-making process has become even more prominent. In such an environment, it is undeniable that AI will significantly assist individuals and investors in making faster and more accurate decisions. AI's ability to think and solve problems like a human can offer realistic solutions, especially in areas such as financial modeling, investment, savings, and e-commerce (Lin, 2024). These skills are important in terms of AI being a significant component of the financial system and, therefore being able to guide individuals and institutions on financial matters.

Applications of Artificial Intelligence in Financial Sytems

In the financial literature, there are four fundamental dimensions that address the integrated use of artificial intelligence and financial systems. These are, in order: customer-facing applications (e.g., insurance services, credit scoring, customer service robots), financial management-level applications (e.g., risk management, market analysis, and capital optimization), financial market activities (e.g., trading and portfolio management), and finally regulatory requirements (Imandojemu et al., 2025).

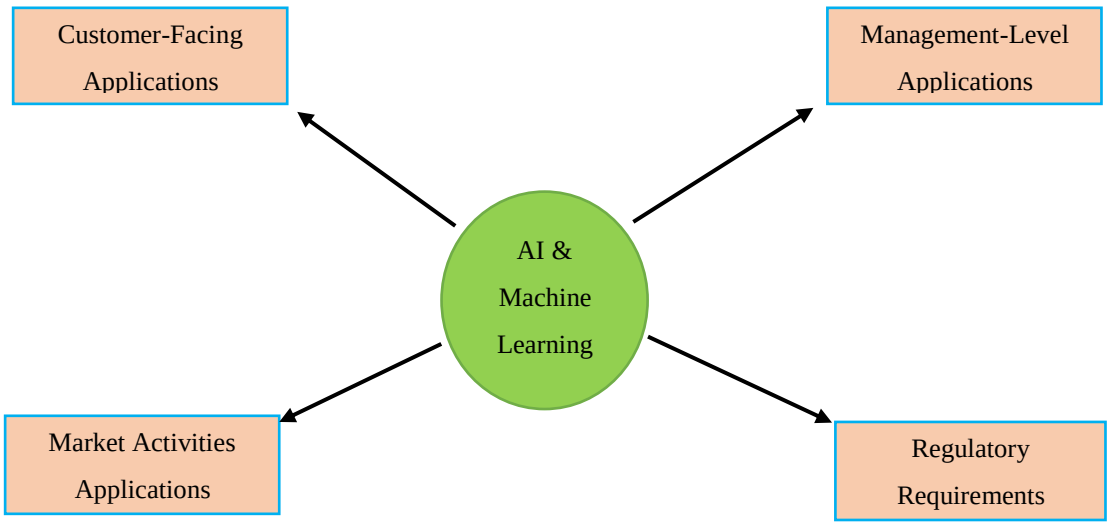

Figure 2. AI Applications in Financial Systems
Source: Imandojemu et al., (2025)

The dimensions shown in Figure 2 form the basic framework for AI applications in financial systems. There are some financial issues below these dimensions that are more easily resolved with AI. These issues and the support services provided by AI for solving them are listed below (Lim, 2024):

- *Trading and investment strategies* → Data analysis, optimization techniques, machine learning, and risk analytics (Ielasi et al., 2020; Ullah et al., 2021; Erhardt, 2020).
- *Portfolio optimization* → Deep learning, reinforcement learning, optimization models, and recommender systems (Meier & Danzinger, 2022; Shea et al., 2021).
- *Automated and smart investment* → Ranking model learning, sequential decision learning, behavior analysis, game theories, deep learning models, and optimization techniques (Sokolov et al., 2021; Yang et al., 2020; Katterbauer et al., 2022).
- *Market Anomalies* → Behavior analytics, event sequence modeling, pattern mining, probability-based modeling, clustering, and classification (Clarkson et al., 2020; Goloshchapova et al., 2019; Raman et al., 2020).
- *Environmental, social, and governance (ESG) metrics* → Dynamic process and programming, machine learning, and deep models (Briere & Ramelli, 2021; Chang & Lee, 2019).
- *Corporate finance* → Time series analytics, outlier detection, numerical methods for optimization, probability-based learning, risk analysis, and labelled and unlabelled learning (Tanthanongsakkun et al., 2023; Teoh et al., 2019).
- *Simulation of market systems* → Computer simulation, agentbased modeling, multiagent systems, human-machine interaction, behavior modeling, and visualization (Geissler et al., 2022).
- *Automated banking and payment systems* → Machine learning, decentralized learning, deep learning and security informatics (Nguyen et al., 2023).
- *Financial services—Insurance* → Profiling, categorization, probability-based and mathematical modeling, anomaly detection, reinforcement modeling, social media analysis, and deep learning (Sætra, 2022; Duchin et al., 2022).
- *Financial services—Internet finance* → web-network analysis, dynamic user modeling, relational modeling, prediction, decentralized learning, and anomaly detection (Vergara & Agudo 2021).
- *Blockchain systems and mechanisms* → Agent-based modeling, algorithmic game theory, representation learning, machine learning, deep learning, semantic web and optimization methods (Yu, 2022; Jebamikyous et al., 2023).
- *Blockchain security* → Process analysis, anomaly detection, event analysis, variation detection, decentralized learning, security informatics, and fraud detection (Choithani et al., 2023).
- *Risk management* → Risk analytics, classification, clustering, semi-labelled learning, event analysis, deep neural techniques, and sequential decision learning (Yang et al., 2022; Roy & Shaw, 2021).
- *Credit management* →Profiling, forecasting, prediction, sequential and recurrent modeling, reinforcement learning, risk analytics, and optimization (Mansouri & Momtaz, 2022; Brogi et al., 2022).
- *Valuation* → Machine learning, probability-based and statistical learning, data analysis, optimization models, pattern mining, evolution-based computing, and social media analysis (Sætra, 2022; Dugo, 2021; Duchin et al., 2022).
- *Forecasting* → Sequential modeling, knowledge discovery, dynamic modelling and programming, machine learning, and deep models (Anas et al., 2020; Ashley et al., 2021).

Maturity Status of Artificial Intelligence (AI) in Financial Industry

The application areas and maturity status of artificial intelligence in the industry, which consists of the main components of the financial system such as banking, capital markets, insurance, payments, and investments, are shown in Table 1. These components are located in offices according to their operational conditions.

Table 1. Maturity Status of AI in the Financial Industry

Offices	AI Applications	Maturity Status
Front Office	Chatbots	More Mature
	Voice Assistants	Less Mature
	Authentication and Biometrics	Less Mature
Middle Office	Monitoring	Less Mature
	Anti-Fraud & Risk	More Mature
	Complex Legal & Compliance Workflows	Less Mature
Back Office	Credit Underwriting	More Mature
	Alternative Data in Trading and Assets Management	More Mature
	Risk Underwriting	More Mature
	Smart Contracts Infrastructure	Less Mature

Source: Adapted from Arsyad et al. (2025)

Explainable Artificial Intelligence (XAI) Methods in Finance

One of the concepts that paves the way for the applicability of AI in finance is Explainable Artificial Intelligence (XAI). XAI is an AI tool used to address the complexities of AI models, particularly when explaining large datasets. The primary goal of XAI is to uncover the black box aspects of AI that are not observable. It also has the following sub-goals (Weber et al., 2024):

- *Trustworthiness:* Expressing the degree of confidence that a model will respond as expected to a specific problem.
- *Causality:* Finding cause-and-effect relationships that expand the scope of the model.
- *Transferability:* Identifying the limitations of the models.
- *Fairness:* Ensuring that the unethical and unfair use of model results is prohibited.
- *Informativeness:* Specifying the distinctions between human-centered decision-making and the problem solved by the model. It relates to the model's inner mechanics.
- *Confidence:* Describing the robustness and stability of a model.
- *Accessibility:* Ensuring end-users' involvement in the AI modeling process.
- *Interactivity:* Improving XAI models by addressing the level of interaction between end-users and XAI models.
- *Privacy awareness:* Informing users to shed light on potential privacy violations.

Explainable Artificial Intelligence (XAI) methods commonly used in finance domains are listed as; SHAP, LIME, Counterfactuals, Partial Dependence Plots (PDP), PASTLE, CASTLE, MANE, LTreeX, DALE, and TREPAN (Martins et al., 2023). These methods are defined in Table 2.

Table 2. Definitions of XAI Methods

Methods	Definitions
SHAP	SHAP is a model-agnostic method providing explanations both on a local and global scope (Chromik, 2021).
LIME	LIME is a model-agnostic technique that provides explanations on a local scope (Ullah et al., 2022).
Counterfactuals	Counterfactuals are approaches that present "what if" scenarios by changing some values in the model, thereby providing new insights into the model (Molnar, 2022).
PDP	Partial Dependence Plots (PDP) is a method that helps interpret how one feature affects another. With this method, a target feature is specifically associated with and explained through a visual presentation. (Friedman, 2001).
PASTLE	PASTLE is an approach that enhances interpretability by reducing the sampling area to pivots or points (La Gatta et al., 2021a).
CASTLE	CASTLE is a method that identifies clusters in data with common behavior and classification and reaches a conclusion by extracting rule-based explanations (La Gatta et al., 2021b).
MANE	MANE is a technique that extracts cross-features by processing the features in a model and then approximates the nonlinear decision boundary by applying linear regression (Tian & Liu, 2020)
LTreeX	LTreeX is a local approach that directly creates a proxy model from Random Forest and explains the outcome of any example (Dedja et al., 2023).
DALE	DALE is an XAI technique that enables calculations performed by the Area of Local Effect (Gkolemis et al., 2023).
TREPAN	TREPAN is a method that enables explanations for the target feature by creating decision trees at the cluster level (Martins et al., 2023).

Source: All sources are located in the Table 2.

Conclusion

The ease of use of AI in daily life has also impacted the financial systems, which are fueled by digitalization and technology. AI's ability to quickly meet the financial needs of actors in the financial system (including investors, savers, regulators, and supervisors), such as examining, monitoring, and analyzing large-scale financial data, has made it even more popular. Therefore, this chapter has been written to explore the applications of AI in financial systems. With this purpose, the development process of AI and applications of AI in financial sytems has been addressed firstly. Additionally, it was stated that financial topics such as trade and investment strategy, portfolio

configuration, automated and intelligent investment, market anomalies, corporate finance, market calibration, automated banking and payment systems, financial services, blockchain systems and their setup, risk management, credit management, valuation, and forecasting can be solved by AI. Lastly, the maturity status of AI in the financial industry and explainable artificial intelligence (XAI) methods in financial areas was described in detail. It is believed that this study, which addresses the position and application areas of artificial intelligence in financial systems, will provide a vision for future academic research, businesses in the financial sector, and actors in financial systems. This perspective can be further deepened, and the knowledge and experience in this field can be made more objective by supporting it with experimental studies to be conducted in the future.

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The interdisciplinary applications of artificial intelligence are reshaping the landscape of modern research and innovation. This book, designed to this end, integrates AI into various fields, unlocking new dimensions of problem-solving in the relationships between active sectors and with each other, and fostering interdisciplinary intellectual growth through this synergy.

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Suitable for all user profiles, this book aims to inspire new research and innovative applications in practical areas of the interdisciplinary use, potential, and future of AI.

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