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The Smart Life Revolution

Embracing AI and IoT in Society

Edited by Connie Tee, Thian Song Ong and Md Shohel Sayeed

The Smart Life Revolution

This book explores the integration of Artificial Intelligence (AI) across areas such as IoT, big data, healthcare, business, economics and security, and improving the quality of life (QoL) in smart cities today.

By looking in depth at the different application areas of AI, the reader learns about the broad and impactful ways AI is transforming our world, its profound influence in enhancing service efficiency, personalisation, accessibility and fostering both scientific and social advancement. The editors consider the importance of bridging theory and practice by offering a practical understanding of how key AI technologies can be applied in real-world scenarios for QoL. By covering both foundational concepts and advanced applications with case studies and practical examples, this approach ensures the reader obtains a comprehensive understanding of the technologies and their impact. An innovation mindset is emphasised with discussion about the challenges, opportunities, future trends and potential research directions to prepare readers for ongoing technological advancements. The book takes an interdisciplinary approach by integrating knowledge from computer science, engineering and social sciences, to offer a holistic view of technology's role in society.

This book serves as a valuable resource for both undergraduate and postgraduate students in the study of AI applications in society. The book may be used by researchers and communities to identify the different challenges associated with key technologies for building new applications for improving the quality of life in smart cities.

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1

Resilience Thinking Artificial Intelligence Integration Framework

Umar Ali Bukar and Radhwan Sneesl

Introduction

Society is rapidly moving towards an era of coexistence between humans and artificial intelligence (AI). This technological advancement is revolutionising various industries, including healthcare, education, finance and transportation, by enhancing the accuracy and efficiency of numerous tasks. However, alongside these benefits, AI also raises significant ethical concerns, creating a complex ethical landscape across different sectors (Tippins et al., 2021; Gaur & Sahoo, 2022; Li et al., 2022; Guleria et al., 2023; Dwivedi et al., 2023; Salloum, 2024; Bukar et al., 2024b, 2024c, 2024d, 2024a). When used efficiently and effectively, AI solutions have the potential to optimise quality of life, foster innovation and reduce environmental pressures. The continuous integration of AI into our daily lives has led to the development of solutions designed to improve user convenience and satisfaction. Tools like ChatGPT and Bard are examples of AI technologies that demonstrate the capability to interact and respond like humans. Today, AI is recognised as a key driver of the future, significantly influencing the development of smart cities and intelligent living environments.

The term "artificial intelligence" is a buzzword that describes a complex intelligent system that behaves or answers like a human, or that is associated with both a property or quality to perform this certain capability (Samoili et al., 2020; Gabriel, 2020; Legg & Hutter, 2007). An intelligent system refers to an advanced computer system that can gather, analyse and respond to data from its environment, and can learn from experience and adapt accordingly. As a result of its capability, AI has become a strategic area of importance and is identified as a potential key driver of economic development, as highlighted in the European strategy on AI (Samoili et al., 2020). Similarly, AI has become a priority for national governments across various countries, resulting in the formulation of dedicated AI strategies. However, discussing

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AI necessitates considering various aspects, this chapter aims to provide an overview of the global AI landscape, focusing particularly on the concept of resilience in the face of rapid AI advancements and how resilience can be used to counter the development of AI effectively.

Accordingly, the chapter introduces the concept of resilience as a critical framework for navigating the AI landscape and ensuring a sustainable future. Resilience, in this context, refers to the ability of systems and societies to absorb, adapt to and transform in response to the changes introduced by AI technologies. This concept was motivated by existing work (Bukar et al., 2024b) through the concept of Risk, Reward, Resilience (RRR) framework (Robert, 2023). The RRR framework suggests that merely considering risk or reward in isolation when creating or introducing policy is insufficient; policymakers must internalise both elements and understand how they interact with and impact resilience over time. This understanding is crucial for determining the likelihood of survival and success in a sustainable society due to AI advancements. While risk, reward and resilience are interconnected, this chapter discusses resilience thinking as the central focus when considering the societal impacts of AI.

Background

The progression of AI brings with it a myriad of ethical concerns that extend beyond what many could have imagined, prompting numerous stakeholders to call for a reassessment of AI initiatives (Tippins et al., 2021; Gaur & Sahoo, 2022; Li et al., 2022; Guleria et al., 2023; Dwivedi et al., 2023; Salloum, 2024; Bukar et al., 2024b, 2024c, 2024d, 2024a). Historically, technological advancements have often sparked significant concerns. For instance, the introduction of cars led to the development of seatbelts to curtail accidents (Robertson, 1996; Cohen & Einav, 2003), electricity brought about rigorous regulations to ensure safety (Huber, 1986; Alonzo, 2009), and the advent of printers and social media raised issues regarding misinformation (Bertot et al., 2012; Posetti & Matthews, 2018), leading to the creation of new norms, laws and institutions to mitigate these risks. Drawing from past experiences with technology, it becomes clear that to address the challenges posed by AI tools, there is a need to establish norms, regulations, practices and institutions designed to ensure society can withstand potential threats from AI, a concept referred to "resilience" in this chapter. Hence, "resilience" is not just about surviving disruptions but also about thriving amidst them. It is about building systems and societies that can adapt to new challenges and leverage them as opportunities for growth and innovation. In the context of AI, resilience involves the capacity to absorb the ethical and operational challenges posed by AI, adapt to these changes, and transform societal structures to better integrate AI in a way that aligns with human values and goals. As AI tools continue to evolve and impact various practices, resilience thinking becomes essential. As a result, the proceeding discusses the AI architecture, applications and integration, as well as the Resilience Thinking Artificial Intelligence Integration Framework.

AI Architecture

The framework of AI Architecture is shown in Figure 1.1, devised from the work of Dong et al. (2020) where AI acts as a critical component within various domains of modern society, such as safety, healthcare, education, legislation, environment, and politics or government (see AI application areas in Figure 1.2 and AI Integration in Figure 1.3). These interdisciplinary factors can either constrain or promote the development of AI systems, reflecting the interconnected nature of AI in societal progress. The core structure of AI Architecture is composed of three layers surrounding the stakeholders: infrastructure layer, technology layer and service layer. The outermost layer

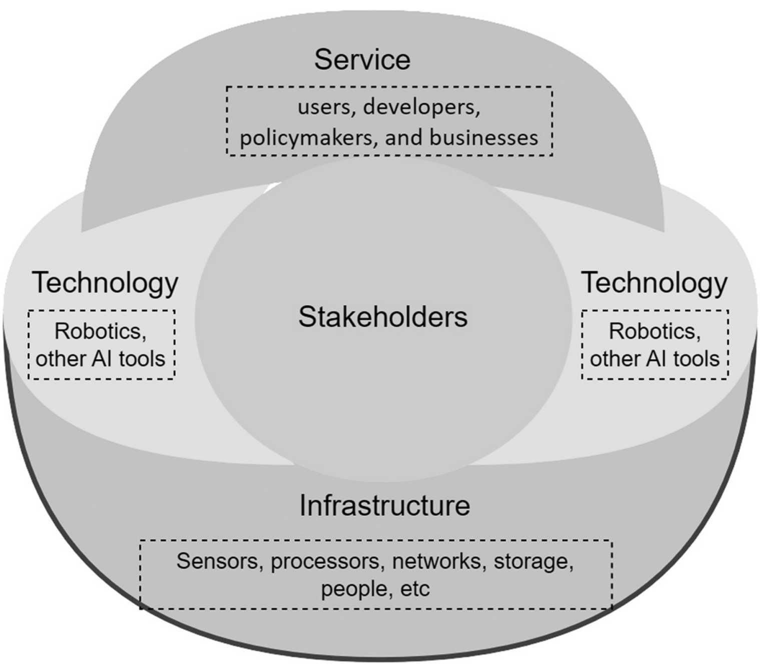

FIGURE 1.1
The AI Architecture, emphasising its foundational layers, stakeholder interactions, and how AI services are structured to meet diverse needs within society.

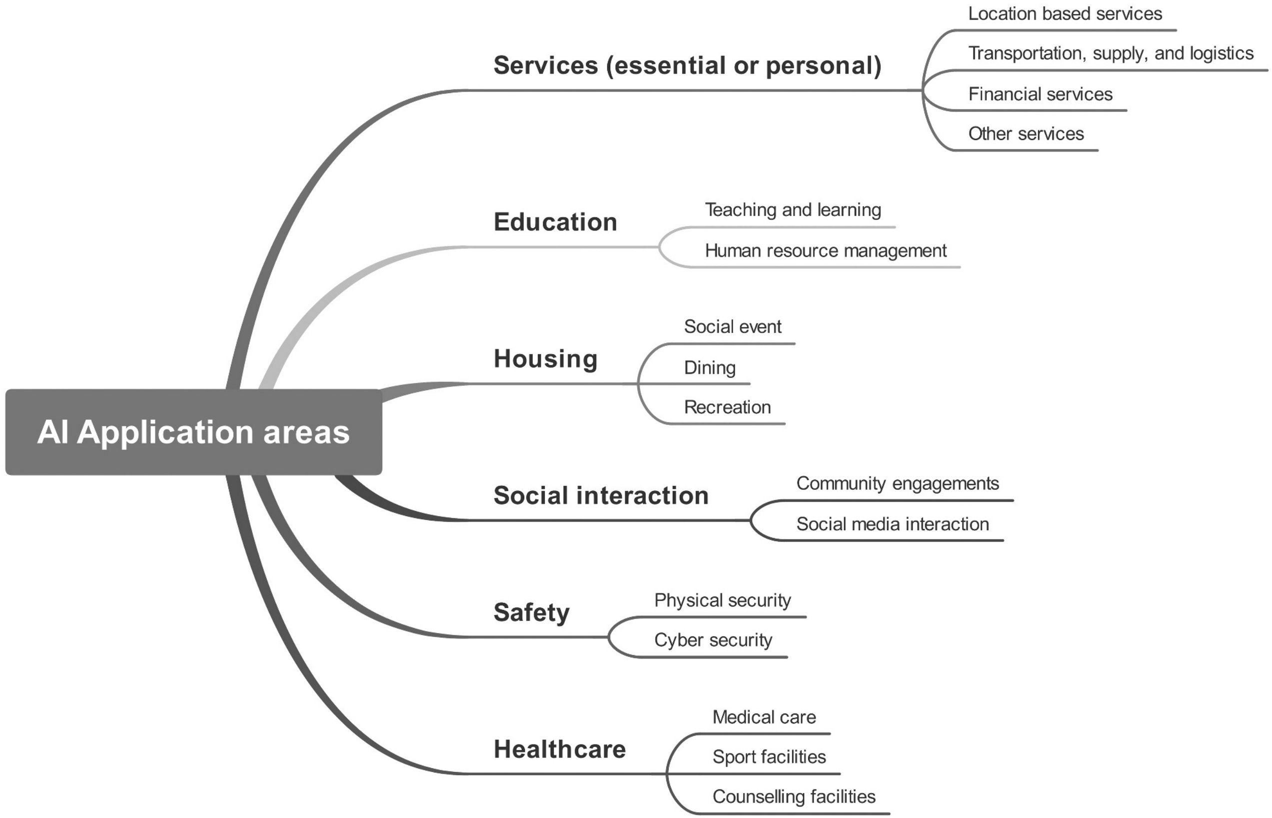

FIGURE 1.2
Perspectives of AI Applications Areas in the Society.

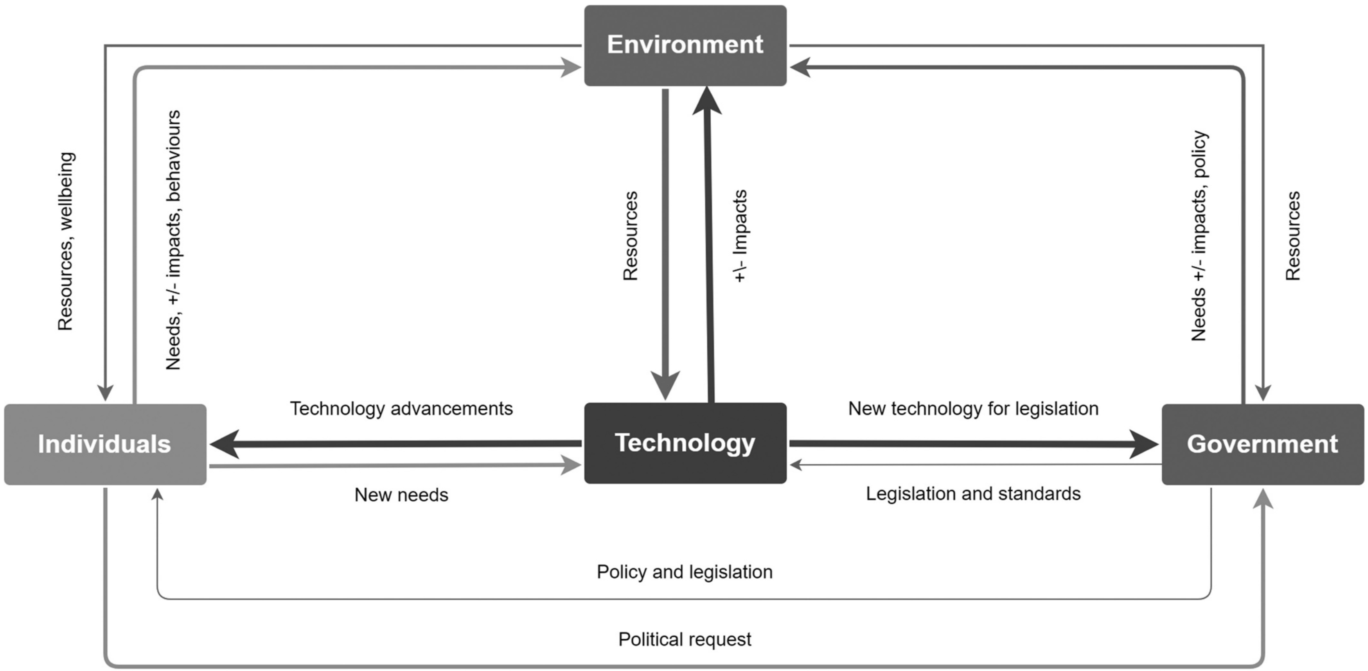

FIGURE 1.3
Schematic representation of the agents and their roles towards the development of AI: The diagram represents the roles and interactions between technology, individuals, government and the environment, and it places more emphasis on the feedback loops and systemic impacts, which align with AI's transformative role in society.

provides the underlying infrastructure essential for AI systems, while the innermost layer includes elements that directly interact with stakeholders. The framework places stakeholders at the centre, signifying that while not all AI system activities directly connect with them, they should be designed with the stakeholders' interests as the focal point. The specific needs of the stakeholders and the three layers of AI Architecture are further elaborated in the following paragraphs.

AI Stakeholders

The planning, development, maintenance and deployment of AI systems involve multiple stakeholders, including users, developers, policymakers, businesses and society at large. Feedback from these stakeholders is vital for the evolution of AI development. Given the diverse roles and contributions of each stakeholder group, it is crucial to fully understand their perspectives to maximise the value and potential of AI. The needs and contributions of each type of stakeholder within AI systems can vary, and an inclusive approach ensures that AI solutions are both robust and aligned with societal needs.

Infrastructure Layer

A strong and adaptable infrastructure is essential for AI development, as it forms the foundation for the other layers. This infrastructure must include both technological components (such as computing power, data storage and communication networks) and human resources (engineers, data scientists and system architects) who design, build and maintain AI systems. The required infrastructure might involve cloud-based solutions, distributed networks, high-performance computing clusters and data centres, ensuring that AI systems can operate efficiently and at scale. New AI infrastructures could be built from scratch for emerging applications, allowing developers to integrate cutting-edge AI technologies from the beginning. Alternatively, existing infrastructures can be retrofitted to support AI functionalities, leveraging the current systems while introducing upgrades that balance cost, performance and scalability. This phased approach is crucial for organisations transitioning from traditional systems to AI-enabled architectures, ensuring that resources are allocated effectively to achieve the desired level of AI capability.

Technology Layer

The technology layer is the intermediary between the infrastructure and the direct applications of AI-facilitated services. Although it may not engage stakeholders directly, it plays a critical role in enabling AI systems to function smoothly. This layer includes algorithms, models, and data processing technologies that form the backbone of AI systems. By leveraging this layer, AI applications can transform traditional processes and overcome obstacles such as limitations in speed, accuracy and scale. Accordingly, the implementation of AI technologies will vary based on specific applications and contexts, as different environments and industries have unique requirements. For instance, AI systems deployed in healthcare may focus on predictive diagnostics and personalised medicine, while those in transportation may emphasise real-time navigation and autonomous systems. The effective deployment of AI technology depends on optimising resources, ensuring privacy and enhancing security while addressing budgetary and operational constraints.

Service Layer

The service layer comprises the AI applications that directly interact with stakeholders. In this context, AI systems should be designed to meet diverse stakeholder needs while achieving their primary objective such as delivering improved and more efficient services. The stakeholder-centred approach in AI systems means that services must be tailored to the specific use cases and preferences of individuals, businesses and organisations. Understanding stakeholder requirements involves gathering data through surveys, user feedback and real-world case studies, which inform the ongoing refinement and development of AI services. Moreover, the primary aim of AI services is to enhance the performance and outcomes across sectors. Whether it is improving customer experiences in e-commerce, streamlining processes in manufacturing, or optimising decision-making in government, AI services should be evaluated based on their ability to contribute directly or indirectly to achieving the desired outcomes. This requires careful assessment of the risks, benefits and potential impacts of each AI service and addressing different aspects of stakeholder needs.

AI Applications

The primary objective of any AI system is to enhance human life by delivering more efficient, personalised and intelligent services. AI is no longer just a buzzword; it has become an integral part of our daily lives, influencing diverse sectors such as transportation, healthcare, banking, retail, entertainment and e-commerce. As highlighted by Min-Allah and Alrashed (2020), various services and applications are now revolutionising intelligent and smart solutions, offering unprecedented advancements in service delivery. Significant projects, like enabling secure electronic transactions through cashless payments and e-wallet systems using smart cards and devices, have become defining features of modern living, powered by AI technologies. These innovations streamline daily interactions and facilitate convenience on a broad scale. With the rapid pace of technological progress, even intelligent solutions quickly become outdated. Many institutions are now incorporating AI-based services, such as facial recognition systems, into their operations. An example is live audio translation services, which enhance accessibility in conferences, theatres and public spaces. Accordingly, data derived from social interactions and networking platforms can be analysed for insights, driving intelligent decision-making. The ultimate goal of any society is to enhance the quality of life and well-being, making AI solutions essential for optimising daily activities and improving public services.

Real-time data fed to AI-powered dashboards enables organisations to make informed, data-driven decisions. AI technologies can also be integrated with existing physical infrastructure to deliver enhanced services. For example, AI-enabled surveillance cameras in buildings can predict structural durability, helping determine when maintenance is required. Also, smart occupancy tracking helps monitor building usage and improves safety during emergencies by providing real-time data on the number of people in a specific location. This can be crucial in disaster situations like fires, tsunamis or earthquakes, allowing for efficient recovery planning, particularly if vulnerable individuals or valuable resources are present. Similarly, AI attendance systems in schools can use smart classroom cameras to automatically mark students' presence, improving efficiency by saving time and streamlining resources for better use. For real-time decision-making, AI-driven systems can be employed across various sectors. For instance, in public spaces, AI-based navigation tools can assist individuals in finding routes or services, while personalised notifications can be sent to citizens about changes in local events or infrastructure updates. Likewise, public safety can be enhanced through AI-powered surveillance systems, such as smart cameras capable of real-time threat detection and analysis. To ensure these applications maintain user trust, the implementation of privacy-preserving AI technologies is crucial. Blockchain-based approaches are gaining traction for safeguarding data integrity and privacy, particularly in smart cities and other AI-integrated communities. These methods provide transparent and secure ways to handle sensitive information without compromising individual rights.

All the core application areas of AI are essential components of a well-functioning AI-powered ecosystem. Insights gained through AI applications can aid governments and organisations in strategic planning. For instance, AI in transportation systems can issue alerts to commuters about service schedules and provide statistical analysis of traffic flow, usage patterns and peak times. Similarly, updates regarding changes in public services or events can be delivered in real time through AI-powered platforms. In addition, smart mobility is one of the leading features of AI-driven societies, generating vast amounts of data from ride-sharing services, public transport and traffic management systems. This data can be harnessed for resource optimisation, smoother traffic flow and more effective public service delivery.

AI can also support services such as utility payments, food deliveries and medical services, streamlining everyday tasks. Moreover, AI-driven analytics can foster better social interactions in both physical and digital spaces. By using facial recognition technologies, public behaviour data can be collected and analysed to offer insights that improve community services, safety measures and engagement strategies. Figure 1.2 illustrates how AI supports various areas within a broader societal context, enabling a more connected, secure and efficient community.

Integration of AI

The integration of AI into society is revolutionising the way individuals, businesses and governments operate, creating a more connected and data-driven world. AI technologies are being embedded across diverse sectors, transforming processes, enhancing efficiency and offering innovative solutions to complex societal challenges. This profound shift makes AI more deeply intertwined with everyday life, impacting decision-making, governance and human interactions, which brings both opportunities for growth and the need for careful consideration of its ethical and societal implications. Vinuesa et al. (2020) schematically illustrate the complex interplay between AI and society, as depicted in Figure 1.3, which represents the key agents and their roles in shaping the development of AI, highlighting the dynamic relationships between individuals, technology, government and the environment. The use of thicker arrows in the diagram denotes areas of faster change or more significant influence, emphasising the rate of transformation within certain interactions.

Accordingly, technology, including AI systems and their developers, serves as a primary driver of change, influencing how individuals work, communicate and interact with both each other and their environment. This influence extends to the government, where new technological advancements prompt the need for updated regulations, piloting and testing frameworks to ensure safe and ethical deployment. Additionally, technology developers actively engage with governments through lobbying efforts and policy influence, influencing changes in regulatory initiatives. The interaction between individuals and technology is bidirectional. On one hand, technical developments shape people's daily lives by introducing new tools and systems that alter their behaviour and decision-making processes. On the other hand, individuals create new demands and challenges that push the boundaries of technological innovation, requiring developers to design solutions that address these evolving needs.

Moreover, the government plays a crucial role by enacting legislation and standards to regulate the responsible use of technology. This ensures that AI and other technologies are developed and deployed in ways that benefit society while minimising potential risks. As societal needs shift, individuals increasingly call upon governments to introduce new laws and policies that reflect the evolving technological landscape and address emerging ethical concerns related to AI. Similarly, the environment is an integral component of the AI-society interaction. It provides the natural resources necessary for the development and operation of technology, from raw materials for manufacturing AI systems to the energy required for data processing and storage. At the same time, technology has a direct impact on the environment, both positively (e.g., through the development of AI solutions that mitigate climate change) and negatively (e.g., through the environmental costs of manufacturing and energy consumption).

Moreover, individuals and governments affect the environment through their decisions, actions, and policies. Governments may implement environmental regulations aimed at minimising the ecological impact of AI technologies, while individuals' consumption patterns and technological choices shape demand for resources and influence environmental sustainability. In particular, the environment, acting as the underlying foundation for all interactions, also represents the planetary boundaries, which are the ecological limits within which humanity and technology must operate to maintain a balanced and sustainable ecosystem. The feedback loops between technology, individuals, government and the environment illustrate the complex interdependencies, where advancements in one domain trigger changes in others. This interaction underscores the need for a holistic approach to AI development, such as RTAIF, which is the central focus of this chapter, where technological progress is aligned with social, ethical and environmental considerations to ensure a sustainable future.

Resilience Thinking AI Framework

This section discusses the theoretical framework of the resilience ability of the individual and society as a result of AI integration. The resilience framework can be visualised as a concentric model, where each layer represents a different level of people or organisation resilience to AI integration. These layers are interconnected but can create resilience independently or in combination (Roberts, 2023). Accordingly, at the innermost circle is the absorption. This layer represents the core ability of people and organisations to withstand the challenges posed by AI without significant changes. The absorption layer emphasises stability and immediate response mechanisms that help maintain the status quo. Secondly, adaptation is positioned at the middle circle layer, surrounding the absorption layer. This signifies the ability of people and organisations to adjust and modify their operations and structures in response to AI integration. Adaptation represents flexibility and learning, highlighting how people can change incrementally to better suit new conditions. Thirdly, at the outer circle lies the transformation, which represents the capability of people or organisations to undergo fundamental changes, rethinking and reshaping their core structures and processes. This layer emphasises innovation and long-term strategic changes that can lead to a more resilient future.

Moreover, the white double-edge arrows show the progression from one stage to another, as well as indicate feedback loops, demonstrating that people and organisations can move back and forth between stages as they evolve and face new challenges. Finally, the uttermost layer consists of the external environment, which represents external factors that influence resilience. This could include economic conditions, regulatory frameworks, technological advancements and societal megatrends. Accordingly, Figure 1.4 illustrates the Resilience Thinking AI Integration Framework, known as RTAIF, with its three core components: Absorption, Adaptation and Transformation. Each concentric circle represents a different level of resilience, highlighting how people and stakeholders can respond and evolve in the face of AI existence. Nevertheless, people's resilience as a result of AI integration and usage is built on dynamic capacities that enable people and society to navigate and thrive amidst change. These capacities, as illustrated in Figure 1.4, are essential for maintaining functionality and ensuring continuity in the face of continuous integration of AI, which are seen as threats to society with myriads

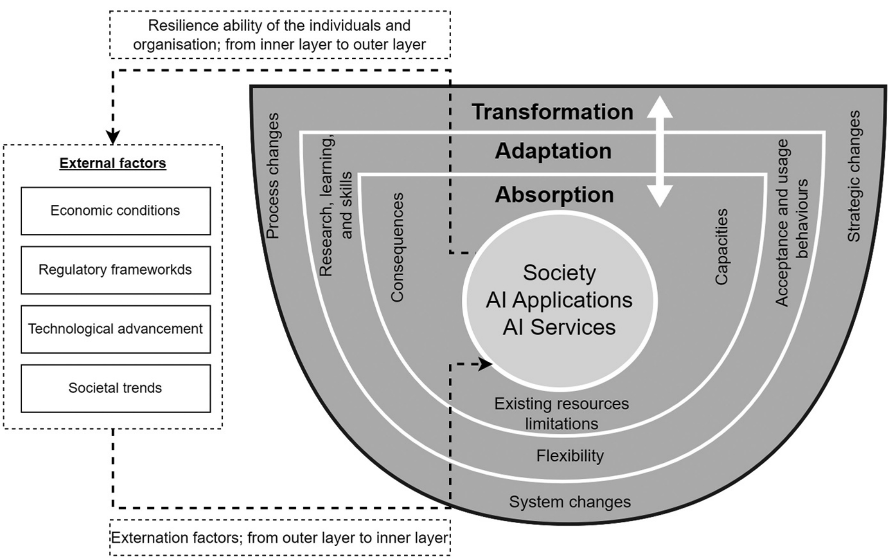

FIGURE 1.4
Resilience Thinking AI Integration Framework (RTAIF), illustrating the three core components; absorption, adaptation and transformation and how external factors influence them.

of ethical concerns. Each of these drivers plays a crucial role in shaping the resilience of the people and society, allowing individuals to withstand, adjust to and evolve from the challenges posed by AI integration in various sectors.

Absorption

Absorption is the first line of resistance that individuals and society exhibit within the resilience framework concerning AI. It represents the ability to withstand the challenges posed by AI without experiencing significant negative consequences. This capacity involves maintaining core functions and structures despite AI integration in various sectors, effectively protecting against immediate impacts. Individuals or organisations with strong absorption capabilities can manage AI-related ethical concerns without substantial changes to their operations or structure. This may involve utilising existing resources (such as experts and detection tools), capacities, and strategies (like policies) to mitigate the potential effects of AI. Accordingly, absorption serves as the foundational layer in the resilience framework, reflecting the capacity of individuals, organisations and societies to handle the immediate impacts of AI while preserving stability. This concept emphasises the ability to sustain core functions and structures in the face of disruptions and ethical concerns brought about by AI integration.

Accordingly, absorption is a key component of the technology integration model, as illustrated in Figure 1.5. Similar to other technologies, the integration of AI involves three stages: adoption – the initial use of the technology in specific contexts; diffusion – the spread of technology across different settings and users; and absorption – the widespread adoption of technology

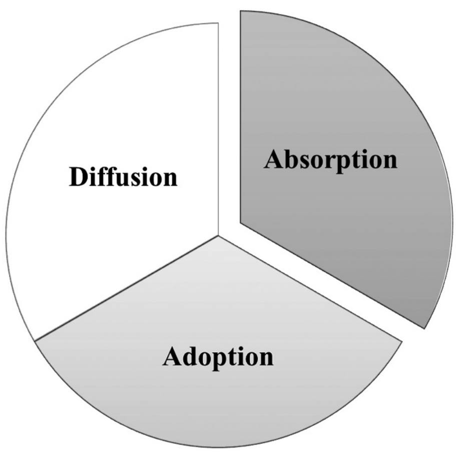

FIGURE 1.5
The three Elements of the Technology Integration Model.

across diverse contexts (Davis, 1989; Rogers, 2014; Venkatesh & Davis, 2000; Ali et al., 2023). The absorption of AI technology is influenced by various factors such as system, organisational, and regional infrastructure, connectivity status, and social and cultural similarities between regions (Ali et al., 2023). The idea of absorption within the resilience framework thus encompasses a broad range of examples and perspectives, highlighting the importance of enduring and managing the initial impacts of AI without major adverse effects. A few examples of absorption across various sectors are discussed as follows:

- Absorption was observed by some universities or academic journals that have introduced strategies to identify AI-generated submissions, and they have also updated their academic integrity codes to explicitly address AI misuse, demonstrating their absorption capacity.
- A hospital that introduces an AI-based diagnostic tool might initially encounter resistance from staff concerned about job security or the accuracy of AI predictions. However, through proper training, transparent communication and gradual implementation, the hospital can absorb these concerns, allowing staff to see AI as a complementary tool rather than a threat.
- A bank using AI to detect fraudulent transactions might face challenges such as false positives or privacy concerns. However, by continuously refining the bank's AI algorithms and maintaining transparency with customers about data use and protection, the bank can absorb these issues without significant disruptions to its business operations or customer trust.
- A manufacturing factory introducing AI-powered robots for assembly line work might face initial pushback from workers fearing job losses. However, using a phased approach to integration, offering retraining programmes and involving employees in the transition process, the company can absorb these concerns and maintain a stable workforce.
- The recent EU AI Act that aims to harmonise rules on AI by following a "risk-based" approach is the first global AI Act, which set a global standard for AI regulation. This helps prevent misuse while still allowing the beneficial aspects of AI, such as enhanced public safety, to be realised.

Adaptation

Adaptation goes a step further than absorption by allowing individuals or organisations to respond proactively to the ethical issues and concerns associated with AI integration. Unlike absorption, which aims to maintain the status quo, adaptation involves making changes that enable individuals and organisations to continue functioning, albeit in a modified form. This capacity is essential, especially given the enduring presence of AI and the ongoing coexistence between AI and humanity, which necessitates continuous adjustments. Moreover, adaptation is marked by flexibility and the ability to modify existing practices, strategies and structures to suit new conditions. It requires learning from past experiences, recognising emerging patterns and implementing changes that enhance the individual and organisation's ability to cope with ongoing or future challenges. Adaptive communities are characterised by their ability to pivot and reconfigure resources and processes to align with changing circumstances. A key strategy in adaptation is conducting research and generating knowledge to understand the behaviours of AI users and their integration, thereby fostering the development of more responsible AI. As a crucial aspect of the resilience framework, adaptation extends beyond simply absorbing the impacts of AI integration. It involves actively adjusting to new circumstances by altering behaviours, strategies and structures to better align with the evolving technological landscape. This proactive approach enables individuals, organisations and societies not only to cope with AI-related challenges but also to harness AI's benefits more effectively.

The typical adaptation policy cycle (Leitner et al., 2020) is presented in Figure 1.6. The end goal is to enhance people and organisation adaptive capacity, strengthen resilience and reduce individual vulnerabilities due to AI integration. Given the impact of AI integration, the question is not whether

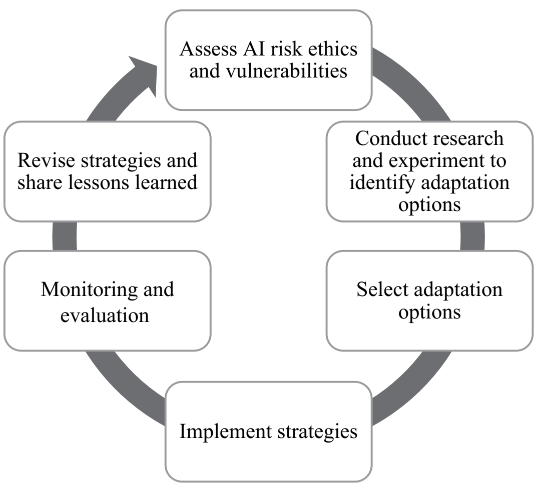

FIGURE 1.6
Adaptation Policy Cycle for AI Integration.

adaptation is necessary, but what are the adaptation options to increase public resilience. The discussion of adaptation within the resilience framework can reveal how various sectors apply these principles in practice and gain insight into how they adjust to the ever-changing technological environment enabled by AI. A few examples are covered in the following:

- Universities that have faced challenges with Gen-AI tools (ChatGPT, Gemini, etc.) generated content (such as essays written by AI tools) might adapt by shifting from traditional written assignments to more interactive, discussion-based assessments. They might also incorporate AI literacy into their curricula, teaching students not only how to use AI tools effectively but also how to critically assess AI-generated information for biases and inaccuracies.
- A hospital might adapt to the introduction of AI diagnostic tools (Google DeepMind's Streams, Zebra Medical Vision, etc.) by changing its workflow to include AI-assisted diagnosis as a preliminary step, followed by human review.
- Financial institutions might adapt to AI's capabilities by incorporating machine learning algorithms into their fraud detection systems, which adaptively learn from new fraud patterns to prevent losses.
- A manufacturing plant might adapt to AI integration by reconfiguring its assembly lines to include AI-powered robots while retraining human workers for roles that require more complex decision-making and oversight.
- A government might adapt to the rise of AI surveillance technologies by introducing new privacy laws that protect citizens' rights while allowing for the beneficial use of AI in public safety (e.g., GDPR, COPPA, EU AI Act).

Transformation

Transformation represents the highest level of resilience to AI integration within society. This stage involves fundamentally altering how individuals, organisations and societies operate, not just to absorb and adapt to changes but to emerge stronger and better equipped for the future. Transformation is about rethinking and reshaping to create new pathways and opportunities, often driven by a desire to address the root causes of AI's ethical issues and build long-term resilience. Characterised by profound and systemic change, transformation is a strategic, proactive process aimed at reinventing how people and organisations function and what they prioritise. This capacity requires visionary leadership, innovative thinking and a willingness to challenge and change existing norms, practices and policies. Accordingly, transformative actions are typically bold and comprehensive, addressing not only immediate ethical concerns but also underlying vulnerabilities and opportunities for growth. This process necessitates deep, systemic changes that fundamentally alter existing structures, behaviours and mindsets. It demands a strategic and forward-looking approach, coupled with a readiness to challenge and reform established norms.

Figure 1.7 presents six necessary conditions for successful transformation for an individual or organisation (Murty and Gorur, 2023). The first condition is communication, emphasising that transparent communication facilitates open, bilateral conversations between leadership and employees, fostering trust and collaboration. Secondly, a change in mindset is essential for digital transformation, requiring individuals to constantly question and challenge current ways of working and to learn new processes and skills. Thirdly, to be adaptable means to embrace new ways of working and to be comfortable in uncomfortable situations, responding flexibly to change. Moreover, people with the right mindset are crucial to transformation success, as they can change practices based on evidence, challenge the status quo, and align with the mission. In addition, selecting appropriate tools and technologies involves understanding the organisation's needs, ensuring efficiency and being open to changing tools as needed. Finally, process improvement argues that identifying and addressing gaps in processes is essential for maintaining high-quality outputs, requiring continuous improvement.

Numerous examples across various sectors illustrate how AI integration has driven transformational change in society, fundamentally altering how

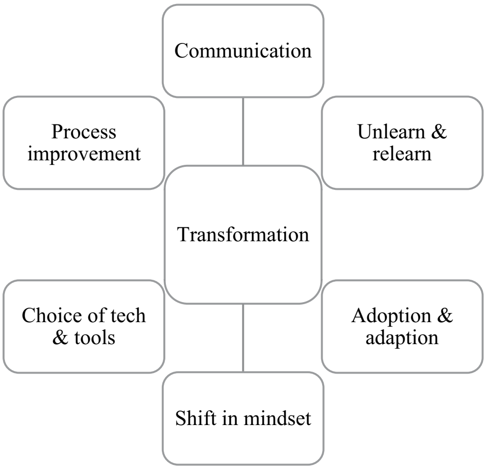

FIGURE 1.7
Six Conditions for Successful Transformation in AI Era.

various sectors are operating and positioning for future success. These examples are briefly explained in the following:

- In education, universities and schools might shift from traditional, knowledge-based curricula to competency-based education that emphasises critical thinking, creativity, and emotional intelligence skills that AI cannot easily replicate. This transformation encourages students to engage in higher-order thinking, problem-solving and ethical reasoning, which are crucial in a world where AI handles routine tasks.
- Healthcare systems are transformed by leveraging AI for predictive analytics to identify at-risk patients and intervene before health issues become severe. This approach shifts the focus from reactive to proactive care, using AI to analyse large datasets and identify patterns that human practitioners might miss.
- Financial institutions might transform by using AI to provide personalised financial advice, leveraging algorithms to analyse customers' spending habits, risk profiles and financial goals. AI can also be used to enhance fraud detection and cybersecurity, transforming the way banks protect customer data and transactions.
- Manufacturing companies can adopt AI-driven automation and robotics, moving towards a "smart factory" model. This transformation goes beyond merely replacing human workers with robots; it involves reengineering production lines to optimise efficiency, reduce waste and enhance product quality.
- Governments could transform by adopting AI to enhance public service delivery, using machine learning algorithms to analyse data and identify areas for improvement in healthcare, education and social services.

Conclusion

The integration of AI into society is inevitable, bringing both opportunities and challenges. This chapter discusses AI architecture, providing insights into key components such as stakeholders, infrastructure, technology and the service layer. Various AI applications are explored across sectors like education, housing, and essential and personal services. Additionally, the chapter examines the interaction between various elements in AI integration, represented by key agents and their roles in shaping AI development. It highlights the dynamic relationships between individuals, technology, government and the environment. Furthermore, this chapter conceptualised a framework, focusing on resilience to better prepare for and adapt to the transformative effects of AI technologies. Emphasising resilience enables societies to not only withstand the challenges posed by AI but also to harness these challenges as catalysts for growth and innovation, paving the way for a sustainable future. The drivers of resilience – absorption, adaptation and transformation – provide a concept for understanding and building resilience amidst AI challenges. The components are not mutually exclusive but rather complementary processes that can occur simultaneously or sequentially, depending on the nature of the issues and challenges and the context of the sectors.

In particular, the absorption within the resilience framework is about readiness and robustness. It involves leveraging existing resources, capacities, and strategies to buffer against the immediate impacts of AI. By enhancing knowledge, connectivity and flexibility, individuals, organisations and societies can develop stronger absorption capacities, enabling them to handle the challenges posed by AI integration effectively. The ability to absorb AI disruptions without substantial alterations to core functions or structures is essential for ensuring a smooth transition into a future where AI plays a central role in various aspects of life. Secondly, adaptation in the context of AI resilience is about more than just coping with change; it's about proactively evolving to thrive in an AI-integrated world. It requires flexibility, the ability to learn from past experiences, and the willingness to modify existing practices and strategies to meet new challenges head-on. By fostering an environment that encourages adaptation, societies can build resilience and ensure that they are not only prepared for the future but also capable of leveraging AI's full potential to drive innovation, efficiency, and positive change. Finally, transformation represents the highest level of resilience, enabling societies to not just survive but thrive in the face of AI integration. The transformation requires a fundamental rethinking of how individuals, organisations and systems operate, focusing on long-term sustainability, ethical considerations and inclusive growth. By embracing transformation, societies can harness the full potential of AI, turning challenges into opportunities and building a future that is resilient, equitable and innovative.

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