LUISS

Department
of Management

Chair of Artificial Intelligence & Digital Marketing

From Business Operations to Smart Cities: How Artificial Intelligence can be Leveraged for Urban Optimisation and Monitoring

Prof. Maximo Ibarra

SUPERVISOR

Prof. Luigi Laura

CO-SUPERVISOR

Matteo Ferracioli

CANDIDATE

Academic Year 2024/2025

Table of Contents

An introduction to AI *11*

What is Artificial Intelligence? 11

A Brief History of Artificial Intelligence 13

Current Developments: How AI is Evolving 14

AI Across Industries: Applications and Impact 16

Chapter 1 - AI for Business Operations: A Foundation for Urban Innovation *20*

1.1 Introduction to Artificial Intelligence in Operations **20**

1.1.1 The Role of AI in Business Operations 20
1.1.2 AI as a Data-Driven Optimisation Tool 22
1.1.3 AI-Powered Real-Time Monitoring and Decision-Making 24
1.1.4 AI-Driven Automation in Business Operations 26
1.1.5 Challenges and Barriers to AI Adoption 29
1.1.6 The Future of AI in Operations 32

1.2 Fundamentals of AI Applied to Business Management **35**

1.2.1 Machine Learning: The Core of AI in Business Management 36
1.2.2 Natural Language Processing (NLP) and AI-Driven Communication 39
1.2.3 Explainable AI (XAI) and Ethical Business Management 41

1.3 Generative AI and Digital Twins **44**

1.3.1 Generative AI: Transforming Content Creation and Automation 46
1.3.2 Digital Twins: Virtual Models for Real-World Optimisation 48

1.4 AI Applications for Real-Time Decision-Making and Process Optimisation **50**

1.4.1 AI for Real-Time Decision-Making 50
1.4.2 AI and Hyper automation in Business Operations 51
1.4.3 AI for Process Optimisation and Resource Efficiency 53

Chapter 2 - AI in Smart Cities: Predictive Maintenance and Transport Optimisation *56*

2.1 Introduction: The Rise of Smart Cities **57**

2.1.1 What is a Smart City? 57
2.1.2 The strategic role of Artificial Intelligence in enabling efficient, sustainable, and resilient urban environments 58

2.2 Predictive Maintenance in Urban Infrastructure **60**

2.2.1 Digital Twins and Internet of Things in Smart cities: Foundations for Predictive Infrastructure Maintenance 60
2.2.2 AI-Powered Algorithms for Fault Detection and Maintenance Scheduling 62
2.2.3 Examples of Application in Everyday Life 64
2.2.4 Benefits: Cost Savings, Reduced Downtime, and Improved Public Safety 66

2.3 AI for Urban Mobility and Transport Optimisation **67**

2.3.1 Real-Time Traffic Management Systems Powered by AI 67
2.3.2 Dynamic Routing, Congestion Mitigation, and Optimisation of Public Transport Timetables .. 70
2.3.3 Predictive fleet management and micro mobility 72
2.3.4 Integration with Mobility-as-a-Service platforms 74

2.4 Environmental and Safety Monitoring through AI **75**

2.4.1 Air quality and noise pollution monitoring using AI and sensor networks 75
2.4.2 AI-powered surveillance for public safety and ethical implications 77

2.5 Challenges and Barriers to AI Adoption in Smart Cities 78
2.5.1 Financial, technical, and organisational constraints 78
2.5.2 Risks related to surveillance, data security, and social inequality 80
2.5.3 The importance of inclusive, citizen-centric AI design 82

Chapter 3 - Case Studies: AI Implementation in Leading Smart Cities 85

3.1 Background and Urban Context 85
3.1.1 Why these cities? 86
3.1.2 Strategic Goals of Smart Transformation 88
3.1.3 Key Stakeholders Involved 89

3.2 Zurich: Pioneering Energy Efficiency and Urban Mobility 91
3.2.1 Overview of Zurich's Smart City Strategy and Goals 92
3.2.2 AI-Driven Street Lighting Management and Mobility Optimisation 94
3.2.3 Technologies Used: IoT, Digital Twins, Adaptive Algorithms 97
3.2.4 Results and Performance Metrics 99
3.2.5 Challenges and Future Prospects 103

3.3 Key Learnings and Implementation Insights 105

Chapter 4 - A Personal Analysis of the Inhabitants' Considerations 107

4.1 Purpose of the Survey 107

4.2 Methodology and Sample 107

4.3 Main Survey Results 108

Conclusion 112

References 115

SUMMARY 133

List of Figures and Tables

Figure 1 – AI composition ... 11
Figure 2 - AGI & ANI ... 12
Figure 3 - AI historic timeline ... 14
Figure 4 - Impact of Ai in the Main Sector ... 16
Figure 5- Estimated Impact of AI on GDP by 2030 ... 18
Figure 6 - AI applications and benefits across key industries ... 19
Figure 7 - Functions and Practical Examples of AI in Operations Management ... 22
Figure 8 - Comparison of Traditional vs AI-enhanced ORM ... 24
Figure 9 - Sector-specific Applications of AI and their Operational Benefit ... 26
Figure 10 - Differences between Traditional & AI-driven Automation ... 29
Figure 12 - Key barriers to AI Adoption ... 31
Figure 13 - Key Ethical Concerns in AI adoption and their Supporting Evidence ... 32
Figure 14 - AI Applications across Key Business Areas and their Expected Benefit ... 34
Figure 15 - Evolution of AI ... 35
Figure 16 - Key Business Applications of Machine Learning: Functions, Benefits, and Techniques ... 38
Figure 17 - NPL: Applications and Benefits ... 40
Figure 18- An Overview of Generative AI and Digital Twin Technologies ... 44
Figure 19 - Core Applications of Generative AI in Business Operations ... 48
Figure 20 - Core Technological Layers of a Digital Twin ... 49
Figure 21- Traditional and Hyper automation ... 53
Figure 22 - Architecture of the Hyperautomation Technology Stack ... 54
Figure 23 - Key Pillars of a Smart City ... 56
Figure 24 - AI Technologies and Their Applications in Smart Cities ... 58
Figure 25 - How AI Supports Smart City Operations: From Data to Action ... 59
Figure 26 - AI Tools and Functions in Predictive Urban Maintenance ... 60
Figure 27 - How Digital Twins Work in Predictive Maintenance ... 61
Figure 28 - Impact of AI Across Infrastructure Domains ... 64
Figure 29 - AI Results Across Urban Infrastructure Domains ... 65

Figure 30 - AI Applications and Sectoral Impact 66
Figure 31 - Cities' technologies and their outputs 68
Figure 32 - AI-Based Optimisation Tools for Public Transport Systems 71
Figure 33 - AI in Urban Mobility 73
Figure 34 - AI Capabilities for User Benefit 75
Figure 35 - AI for Air Quality and Noise Pollution Monitoring 76
Figure 36 - AI Urban Surveillance 78
Figure 37 - Mitigation for Barriers to AI Adoption 80
Figure 38 - AI Deployment Risk in Smart Cities 82
Figure 39 - Challenges of Ethical AI Governance in Urban Environments 84
Figure 40 - IMD Smart City Index 2025: Results In 2025 city ranking order and 2024 comparison 86
Figure 41 - Smart City Index: Global Rankings and Performance Trends 95
Figure 42 - Key Structure Indicator in Zurich 100
Figure 43 - Key Technology Indicators 101
Figure 44 - Challenges and Future Prospects 104
Figure 45 - Could AI improve urban services? 108
Figure 46 - Do you use smart apps? 109
Figure 47 - Would you be in favour of giving up your data? 110

“Men have become the tools of their tools.”

HENRY DAVID THOREAU

Among the most influential innovations of the 2020s, Artificial Intelligence in all its forms certainly deserves an honourable mention. Revolutionising entire sectors, millions of jobs and the lives of everyone, this ground-breaking technology is reshaping economies and redefining the future of businesses worldwide.

It is obvious and normal that such disruptive changes give rise to risks, fears and criticisms. In fact, this is something that AI has suffered from since its outburst, with scepticism from both those who have embraced it as a technology and those who fear it and as a result, avoid it.

But like any technological revolution, the option of simply ignoring or denying the integration of Artificial Intelligence in our society is not possible. Its interconnectedness today has rendered it an indispensable tool for numerous societal systems, not to mention the substantial capital that has been invested in it, underscoring its significance. The only solution is to embrace this revolution and make it a point of strength for businesses, society, and global advancements. Scholars have highlighted the challenges that come with co-designing AI systems with local stakeholders and adapting these systems for long-term societal change. Nonetheless, they have also emphasised the importance of integrating AI into local communities, and the benefits it can generate for community empowerment (Hsu et al, 2022)[1].

A tenuous subject surrounding AI’s integration is the fragility it brings to the future of work and its potential to replace hundreds of thousands of jobs. When it comes to repetitive and automotive tasks that require maximum productivity, it is widely believed that AI has the potential to cause extensive unemployment and job displacement. Nonetheless, human emotional intelligence remains a competence that is irreplicable by technology, therefore an assurance remains on the fact that AI will not supplant human beings in their respective vocations (Adepoju, 2024)[2]. However, multiple scholars have expressed their

[1] Hsu, Y.-C., Huang, T.-H. ‘Kenneth’, Verma, H., Mauri, A., Nourbakhsh, I. and Bozzon, A. (2022). Empowering local communities using Artificial Intelligence

[2] Adepoju, O.D., Tijani, B. and Karera, S. (2024). Artificial Intelligence Skepticism in Career Domains. *International Journal for Digital Society*

alternative perspective, such as Shinde et al. (2021)[3], arguing that AI has the potential to generate novel employment opportunities. These often emerge in sectors that demand oversight, maintenance, and development of AI systems, such as roles in data science, machine learning engineering, and ethical governance. As businesses increasingly adopt AI, there is a growing need for professionals capable of integrating these technologies into existing workflows, training AI models, and interpreting their outputs for strategic decision-making. Consequently, while certain traditional jobs may become obsolete, the evolution of the labour market could lead to a net positive effect, with AI serving as a catalyst for job transformation rather than mere replacement.

Among the sectors that have most understood the competitive advantage in adopting AI in their operations are manufacturing, logistics, and retail: in fact, the introduction of this technology has enabled the study, monitoring, improvement and prediction of almost all aspects of the subject matter dealt with by these companies and sectors.

Ultimately, despite the debates surrounding AI's impact on the future of the workforce, its role as a tool for optimisation and monitoring of operations is undeniable. From enhancing decision-making processes to streamlining workflows, AI continues to revolutionise industries by improving efficiency, accuracy, and adaptability. Cases such as AI's implementation in Plant Operators have shown that decision support systems with this integrated technology can significantly reduce human error, anticipate equipment failures before they occur and optimise energy usage in real time. By analysing vast amounts of data and providing actionable insights, these systems empower operators to make more informed and timely decisions. In summary, as industries continue to embrace digital transformation, AI stands at the forefront of this disruptive change, bridging the gap between data and action, and driving sustainable growth across sectors.

The objective of this thesis is to analyse how the introduction of Artificial Intelligence (AI), initially applied within business operations, can be extended to broader urban contexts such as smart cities, significantly contributing to performance enhancement, risk reduction, and process optimisation. Through a theoretical framework followed by an

[3] Shinde, A., Pawar, D. and Sonawane, K. (2021). Automation in pharmaceutical sector by implementation of Artificial Intelligence platform: a way forward. *International Journal of Basic & Clinical Pharmacology*

empirical application, the study aims to explore the functioning of key AI-based tools, assess their tangible impacts in the fields of mobility and infrastructure management, and reflect on their potential contribution to the sustainable and inclusive development of contemporary cities.

An introduction to AI

What is Artificial Intelligence?

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think, learn, and make decisions. It encompasses a variety of subfields, including Machine Learning (ML), Natural Language Processing (NLP), computer vision, and robotics: these technologies enable machines to analyse data, recognise patterns, solve problems, and make autonomous decisions, often surpassing human capabilities in terms of speed and accuracy (Stryker et al, 2024)[4].

AI is a generic term that regards various computational techniques and approaches. Among these is ML which refers to algorithms that allow data-driven learning to resultantly improve their operational performance without the need for explicit programming. It also contains a more advanced subset, namely Deep Learning (DL), which imitates the structure of the human brain through artificial neural networks.

The analyses and outputs can then be applied through Robotics and Automation, which integrate AI into mechanical systems capable of performing tasks autonomously.

Among the technologies within the AI umbrella lie NLP and Computer Vision, which enable the AI system to understand, interpret and generate human language, as well as process and analyse visual information.

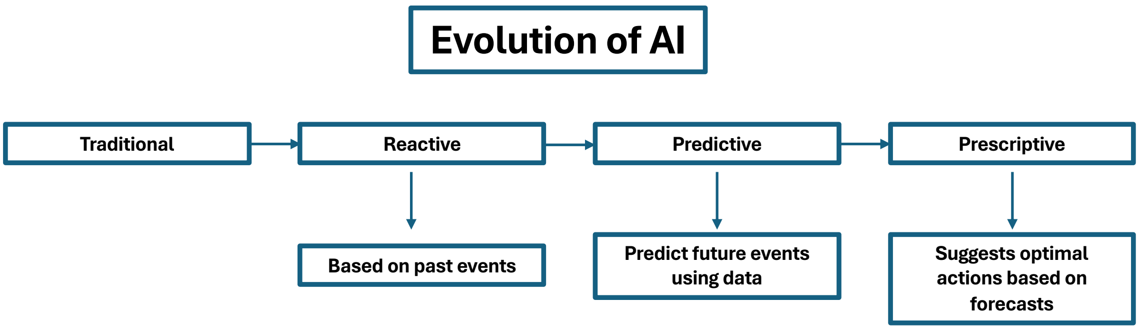

Figure 1 – AI composition[5]

[4] Stryker, C., Kavlakoglu, E., (2024). What is artificial intelligence (AI)? Ibm.com
[5] Source: personal elaboration

Even when it comes to the type of AI, not only is there Artificial General Intelligence (AGI), known as Strong AI, but also Artificial Narrow Intelligence (ANI), known as Weak AI. First off, AGI, formally the more complex model, aims to imitate human intelligence with the objective of performing intellectual human tasks (Sowri, 2024)[6]. This encompasses functions such as reasoning, problem solving and generating creative content and examples of research in this area include projects from DeepMind and OpenAI.

On the contrary, ANI is the more rigid model which operated under pre-defined rules. This version is designed to perform specific tasks, such as speech recognition, and is the more common form that one may encounter today (Sowri, 2024). It is applied to commodities such as Siri and Alexa, as well as recommendation algorithms used by platforms such as Netflix and Spotify. Despite ANI currently dominating in popularity, continuous advances in DL and neural networks are gradually pushing the boundaries towards more autonomous and sophisticated systems.

Ultimately, these systems provide different advantages to the user, with AGI aiming to mimic human-like cognitive abilities, and ANI designed to excel in more specific and specialised tasks (Salecha, 2016)[7].

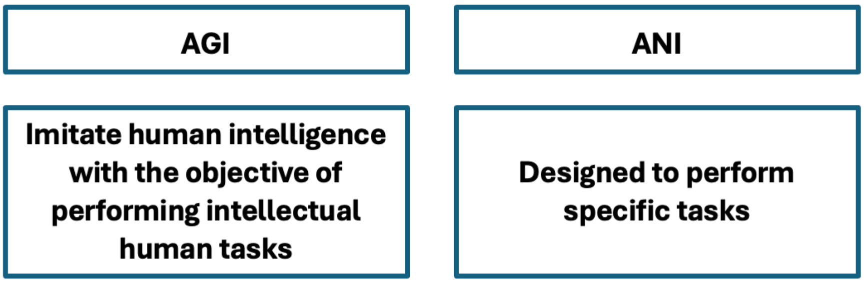

Figure 2 - AGI & ANI[8]

[6] Sowri, M., Banana, K., Com, M. and Phil, M. (2024). A STUDY ON NARROW ARTIFICIAL INTELLIGENCE-AN OVERVIEW

[7] Manisha Salecha (2016). Artificial Narrow Intelligence vs Artificial General Intelligence | AIM Media House. Analytics India Magazine

[8] Source: personal reworking from Manisha Salecha (2016). Artificial Narrow Intelligence vs Artificial General Intelligence

A Brief History of Artificial Intelligence

Artificial Intelligence (AI) has its roots in mathematics, logic, and cognitive science, with key milestones shaping its evolution and although its diffusion has seen exponential growth in recent years, its roots date back over 70 years.

Alan Turing, in the 1950s, proposed the Turing Test, a measure of a machine's ability to exhibit intelligent behaviour, while John McCarthy coined the term "Artificial Intelligence" in 1956 during the Dartmouth Conference, marking the official beginning of AI research.

During the next decade, early AI programs such as Eliza, one of the first typologies of chatbot, and SHRDLU, a Natural Language Processing (NLP) system, showcased AI's potential in human-computer interaction. However, limited computational power and unrealistic expectations lead to the first "AI winter", a period characterised by the reduction of funding and interest for the subject. Additional complications in AI's rise includes the two-time collapse in its lifetime after periods of popular success which makes its history an important learning curve to anticipate the future and follow steps to prevent another winter (Toosi et al, 2021)[9].

It was only during the 1970s that AI research saw a resurgence due to the development of expert systems which used rule-based logic to simulate human decision-making. An example of its early application was in MYCIN, a computer program utilising knowledge for infectious disease applications. A small collection of researchers, most of which had experience in medical decision-making through computational intelligence, began to recognise the need for computer understanding in the field of medicine. They developed a rule-based expert system, formally MYCIN, to diagnose bacterial infections (Shortliffe et al, 1977)[10], which resultantly demonstrated the potential of advancements in this technology through its success.

This revival of interest in research, between the 90s and the 2000s, led the expansion of Machine Learning (ML) and neural networks' leads to major breakthroughs, such as IBM's

[9] Toosi, A., Bottino, A.G., Saboury, B., Siegel, E. and Rahmim, A. (2021). A Brief History of AI: How to Prevent Another Winter

[10] Shortliffe, E.H. (1977). Mycin: A Knowledge-Based Computer Program Applied to Infectious Diseases. Proceedings of the Annual Symposium on Computer Application in Medical Care

Deep Blue defeating chess champion Garry Kasparov in 1997 (Hsu, 2022)[11] and the rise of AI-powered search engines like Google.

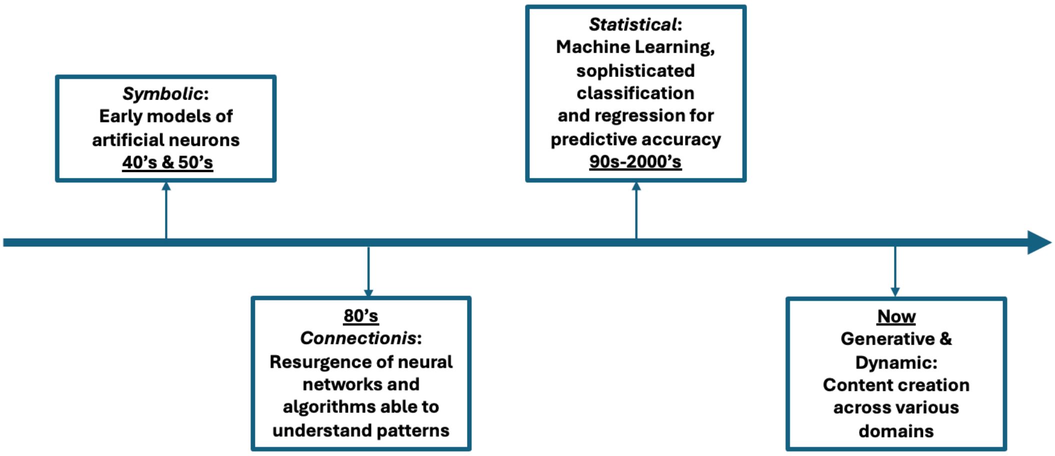

Figure 3 - AI historic timeline[12]

Nonetheless, it has only been in recent years that advances in deep learning, big data, and computational power have enabled AI to reach new levels of sophistication. In 2016, Google's AlphaGo defeated the world's best Go player, showcasing AI's ability to master complex strategy games, while AI now drives autonomous vehicles, revolutionises healthcare, and powers real-time language translation.

It is indeed undeniable that Artificial Intelligence is no longer a futuristic concept but rather an element deeply rooted in everyday life that is transforming sectors and economies at an unprecedented rate.

Current Developments: How AI is Evolving

To analyse and predict how Artificial Intelligence (AI) is evolving, it is necessary to understand which factors are most influential towards its recent development and diffusion. First off, the limited availability of digital data was once a significant constraint

[11] Feng-hsiung Hsu. (2022). Behind Deep Blue
[12] Source: personal elaboration

in the development of AI. Machine Learning (ML) algorithms, but particularly Deep Learning (DL) models, require large and diverse datasets to effectively learn patterns and make accurate predictions. In the early stages of AI, much of the world's information was not digitalised and existing datasets were often too small, narrow, or unrepresentative. They were therefore unable to support robust model training, resulting in poor generalisation, high error rates, and limited applicability beyond controlled environments. This obstacle has been overcome by the exponential increase in digital data availability due to the simultaneous expansion of social media, Internet of Things (IoT) and cloud storage, which provides AI models with unprecedented amounts of information to learn from. However, studies and analyses are underway regarding the reliability and quality of this collected data, due to its risk of containing ambiguous figures which may not be representative over time, therefore skewing outcomes and producing unfair, bias and overall inaccurate results (Inel et al, 2023)[13].

Another huge limitation that is being overcome is the previously insufficient computing power, which resulted in slow model training times and limited scalability.

With the rise of Graphics Processing Units (GPUs) and Quantum Computing (QC), AI algorithms can process complex tasks faster than ever. Furthermore, DL models inspired by the human brain are now increasingly widespread, which allow AI to recognise speech, translate languages and even generate creative content autonomously.

Given these factors, one of the most promising areas of AI research is Self-Supervised Learning (SSL), a technique where AI models autonomously generate training labels from raw data, minimising human intervention and significantly enhancing efficiency, scalability, and adaptability (Rani et al, 2023)[14].

Lastly, Explainable AI (XAI) is a set of techniques and methods that make AI models' decision-making processes comprehendible to humans. It is gaining importance in addressing concerns about AI transparency and bias, as companies are investing in

[13] Inel, O., Draws, T. and Aroyo, L. (2023). Collect, Measure, Repeat: Reliability Factors for Responsible AI Data Collection. Proceedings of the AAAI Conference on Human Computation and Crowdsourcing

[14] Rani, V., Nabi, S.T., Kumar, M., Mittal, A. and Kumar, K. (2023). Self-supervised Learning: A Succinct Review. Archives of Computational Methods in Engineering

making AI more explainable and ethical, ultimately ensuring fair decision-making in critical areas such as finance, healthcare, and hiring (Haque et al, 2023)[15].

Sector	Potential Ai Consumtion Impact	% Adoption Maturity		
		Near term (0-3 yr)	Mid term (3-7 yr)	Long term (7+ yr)
Healthcare	3.7	37%	23%	40%
Automotive	3.7	35%	47%	18%
Financial Services	3.3	41%	59%	0%
Transportation and Logistics	3.2	41%	41%	17%
Technology, Communications and Entertainment	3.1	47%	36%	17%
Retail	3.0	54%	38%	8%
Energy	2.2	39%	44%	17%
Manufacturing	2.2	14%	83%	3%

Figure 4 - Impact of Ai in the Main Sector[16]

AI Across Industries: Applications and Impact

Up to this point, Artificial Intelligence (AI) has been adopted in multiple industries more and more every day, revolutionising workflows, increasing efficiency and opening new possibilities. Among the most revolutionary industry applications lies the Healthcare sector, used in advancements such as AI-based diagnostics (e.g., IBM Watson), robotic surgeries, personalised medicine, and drug discovery. According to McKinsey & Company (2023)[17], AI is estimated to reduce diagnostic errors by up to 30% and accelerate medical research. According to the same study, AI-based risk analysis is now standard in banks and investment firms due to its computational speed and error reduction. The practical

[15] Haque, A.B., Islam, A.K.M.N. and Mikalef, P. (2023). Explainable Artificial Intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research. *Technological Forecasting and Social Change*

[16] Source: personal reworking from PwC, 2023, AI's $15.7 Trillion Impact on the Global Economy, PwC AI Report

[17] McKinsey & Company, 2023, The state of AI in 2023: Generative AI's breakout year, McKinsey Report

application of these systems in the finance sector, can be found in elements such as algorithmic trading, fraud detection, credit risk assessment, and customer service chatbots (McKinsey & Company, 2023).

These features are also widespread in the logistics and transportation sector, stimulating the invention and spread of autonomous vehicles, AI-powered traffic management, and supply chain optimisation. Benefits of these emerging technologies for this industry includes the decrease in costs, the increase in productivity by reducing delivery times, and the improvement of fuel efficiency. In fact, supply chain optimisation is one of the sectors in which the use of AI is growing the most.

Its use is also growing in marketing, advertising, retail, and e-commerce for tasks such as content creation, targeted advertising, sentiment analysis and customer behaviour prediction. In recommendation systems like those of Amazon and Netflix, where dynamic pricing strategies are applied, AI also powers chatbots and tools for customer service and inventory management, helping to optimise sales and gather valuable customer data.

Region	Impactc on the GDP IN %	Impactc on the GDP IN $
China	26,10%	$ 7,0 trillion
North America	14,50%	$ 3,7 trillion
Southern Europe	11,50%	$ 0,7 trillion
Developed Asia	10,40%	$ 0,9 trillion
Northern Europe	9,90%	$ 1,8 trillion
Africa, Oceania and other Asian markets	5,60%	$ 1,2 trillion
Latin America	5,40%	$ 0,5 trillion

Figure 5- Estimated Impact of AI on GDP by 2030[18]

From a monetary point of view, according to PwC's Economic Outlook (2023)[19], AI could contribute $15.7 trillion to the global economy by 2030. This predicted figure is due to AI's productivity gains achieved through process automation, the augmentation of the existing workforce, and the rise in consumer demand driven by both higher-quality AI-enhanced products and services and the novelty of personalization. These factors position AI as one of the most transformative technological advances of the century.

[18] Source: personal reworking from PwC, 2023, AI's $15.7 Trillion Impact on the Global Economy, PwC AI Report
[19] PwC, 2023, AI's $15.7 Trillion Impact on the Global Economy, PwC AI Report

Industry	AI Applications	Key Benefits
Healthcare	Automated diagnostics (e.g., IBM Watson), robotic surgery, drug discovery, personalized medicine	Reduced errors, faster research, tailored treatments
Finance	Algorithmic trading, fraud detection, credit scoring, virtual assistants	Increased speed and accuracy, risk mitigation
Logistics	Autonomous vehicles, supply chain optimization, warehouse automation	Cost reduction, faster deliveries, operational efficiency
Retail & E-commerce	Recommendation engines (e.g., Amazon, Netflix), dynamic pricing, AI chatbots, inventory management	Sales optimization, personalization, customer loyalty
Marketing & Advertising	Content generation, targeted ads, sentiment analysis, automated A/B testing	Higher ROI, data-driven decisions

Figure 6 - AI applications and benefits across key industries[20]

Reflecting upon all these elements, it is deducible that AI is no longer just a tool, but rather a driving force that shapes industries, economies and societies. Therefore, the future challenge is to ensure an ethical, fair and beneficial development of AI that maximises its potential by minimising the risks and increasing the benefits that can be derived from it.

[20] Source: personal elaboration

Chapter 1 - AI for Business Operations: A Foundation for Urban Innovation

1.1 Introduction to Artificial Intelligence in Operations

Artificial Intelligence (AI) is increasingly being adopted by companies, and thanks to this widespread corporate implementation, the technology has evolved rapidly, becoming more efficient, accessible, and adaptable. This accelerated development within the private sector has not only enhanced business performance, but it has also created a solid technological and methodological foundation from which other entities, such as public administrations and urban planners, can now benefit (Chui et al, 2018)[21].

In this sense, the application of AI in business operations represents a crucial stage in its maturity path, where real-time data analysis, automation, predictive systems, and optimisation tools have been tested, refined, and scaled. These same capabilities are now being transferred and adapted to the urban context, where cities face similar challenges in terms of resource allocation, process efficiency, service delivery, and risk management (Batty, 2018)[22]. Therefore, understanding how AI has reshaped business operations allows us to better comprehend its transformative potential within smart cities and how these advanced systems can support the development of more sustainable, responsive, and intelligent urban environments.

1.1.1 The Role of AI in Business Operations

Artificial Intelligence (AI) is fundamentally transforming the way businesses operate by reshaping and redesigning core processes across various departments. Traditionally, operations management has heavily depended on manual supervision, the expertise of experienced professionals, and insights derived from historical data to make strategic decisions. While effective to a certain extent, these methods were often limited by human capacity, prone to delays, and susceptible to errors in judgment or calculation. With the rise of AI technologies, companies are now empowered to move beyond these limitations by leveraging real-time analysis of vast and complex datasets, uncovering

[21] Chui, M., Francisco, S., Manyika, J., San, Mehdi, F., Chicago, M., Henke, N. and London (2018). NOTES FROM THE AI FRONTIER INSIGHTS FROM HUNDREDS OF USE CASES

[22] Michael Batty. (2018). Inventing Future Cities

insights that would be nearly impossible to obtain through traditional means (Selvarajan, 2021)[23]. This shift allows businesses to proactively identify and address operational inefficiencies, such as potential bottlenecks in workflows or supply chains, before they become problematic.

The benefits of this evolution are significant: greater accuracy in decision-making, improved scalability of operations, and enhanced adaptability to rapidly changing market conditions (Morgan Stanley, 2023)[24]. According to McKinsey & Company (2023)[25], AI-driven operations not only reduce the occurrence of human error but also eliminate the time lags that traditionally slowed down decision-making processes. As a result, organisations can achieve a higher level of efficiency, responsiveness, and precision than ever before, positioning AI as a cornerstone of modern business strategy.

A practical and increasingly impactful application of these advanced technological capabilities can be seen in the integration of predictive analytics, real-time monitoring, and process optimisation across various operational domains (Taylor, 2025)[26]. Predictive analytics, for instance, allow businesses to anticipate fluctuations in customer demand, detect early signs of potential machine failures, and foresee disruptions within the supply chain (Selvarajan, 2021). Resultantly, they adopt a proactive approach to risk mitigation and resource planning, enhancing their competitiveness as they increase their responsiveness to market changes. Similarly, real-time monitoring systems continuously analyse live operational data, ensuring that processes remain agile and resilient in the face of unexpected changes or inefficiencies (Wang, 2023)[27].

In addition to these tools, Robotic Process Automation (RPA) plays a pivotal role in streamlining repetitive administrative tasks and back-office functions, significantly reducing human error and increasing operational speed and consistency (Taylor, 2025). These automated systems not only handle high-volume, rule-based tasks with

---

[23] Selvarajan, G.P. (2021) 'Leveraging AI-Enhanced Analytics for Industry-Specific Optimisation: A Strategic Approach to Transforming Data-Driven Decision-Making', *International Journal of Enhanced Research in Management & Computer Applications*

[24] Morgan Stanley (2023) *2023 ESG Report*

[25] McKinsey & Company, 2023, The state of AI in 2023: Generative AI's breakout year, McKinsey Report

[26] Taylor, A. (2025). *How Walmart and Amazon Are Redefining Retail Efficiency with AI-Powered Logistic*

[27] Wang, Y. (2023). *Generative AI in Operational Risk Management: Harnessing the Future of Finance*

remarkable efficiency, but also free up valuable human capital to focus on higher-order, strategic activities. Complementing these technologies are cognitive decision support systems, which harness the power of AI to enhance strategic planning by simulating complex scenarios, evaluating multiple variables simultaneously, and providing data-driven recommendations (Selvarajan, 2021). Together, these AI-powered applications are revolutionising the way organisations operate, rendering decision-making more precise, responsive, and aligned with long-term objectives.

Technology	Function	Example
Real-time analytics	Process large data streams instantly	Demand forecasting
Predictive analytics	Forecast failures or trends	Anticipating supply chain delays
Robotic Process Automation	Automate repetitive administrative tasks	Back-office automation
Cognitive decision systems	Support strategic planning	Scenario simulation

Figure 7 - Functions and Practical Examples of AI in Operations Management[28]

1.1.2 AI as a Data-Driven Optimisation Tool

The adoption of Artificial Intelligence (AI) in operational processes offers significant benefits, primarily through its exceptional ability to process and analyse vast amounts of data in real time. Beyond this, AI thrives on the increasing volume and variety of data available to businesses today, transforming raw information into valuable insights. This enhanced data utilisation empowers organisations to optimise workflows, improve decision-making accuracy, and drive overall operational efficiency with an elevated level of precision.

Unlike traditional analytics which rely on historical data sets, AI analytics leverages Machine Learning (ML) algorithms to identify patterns and predict future trends with greater accuracy and speed. It continuously learns from real-time data streams, enabling companies to detect anomalies, anticipate failures, and optimise workflows proactively.

[28] Source: personal elaboration

In fact, scholars have recognised that operation optimisation through intelligent analysis has become a significant competitive advantage determinant. This is because, as discussed in a Journal by Selvarajan (2021)[29], it assists in lowering costs, improving customer satisfaction, and driving innovation in value creation.

Moreover, by analysing real-time data from sensors and other sources, AI's integration into operations drives significant advancements in predictive maintenance. AI can forecast equipment failures before they occur, allowing for timely interventions which overall ensures smoother operational workflows.

Another critical application is in supply chain optimisation (SCO), where AI models predict inventory needs, transportation delays, and supplier risks, and are widely used by companies such as Amazon and Walmart. These two multinational corporations have revolutionised SCO by integrating AI-powered logistics systems. Walmart employs autonomous robots in its warehouses to efficiently move goods, reducing sorting and shipping times. In the meantime, their AI systems analyse real-time data to adjust their supply chain activities swiftly in response to changing demand patterns, resultantly enhancing operational efficiency. Similarly, Amazon utilise AI to automate its entire supply chain, from inventory management to the order fulfilment process. ML algorithms predict product demand with high accuracy, ensuring optimal stock levels and timely replenishment and AI-powered robots assist in warehouse operations, moving products efficiently to meet demand (Taylor 2025)[30]. These AI-driven strategies enable both companies to deliver products faster and more efficiently, leading to reduced operational costs and enhanced customer satisfaction. Moreover, businesses can maintain healthier cash flows by minimising excess inventory, reducing holding costs, and accelerating the conversion of stock into revenue.

AI is starting to integrate into the world of operational risk management (ORM), helping companies to better navigate the increasingly complex digital landscape. An example is Morgan Stanley piloting GPT-4 into its operations, with the aim to enhance its wealth-

---

[29] Selvarajan, G.P. (2021) 'Leveraging AI-Enhanced Analytics for Industry-Specific Optimisation: A Strategic Approach to Transforming Data-Driven Decision-Making', *International Journal of Enhanced Research in Management & Computer Applications*

[30] Taylor, A. (2025). *How Walmart and Amazon Are Redefining Retail Efficiency with AI-Powered Logistic*

management services. This technological implementation has seen operational improvements in offering a more personalised client service, ultimately enhancing their competitiveness in this customer offering (Morgan Stanley, 2023)[31].

Aspect	Traditional ORM	Generative AI-enhanced ORM
Data handling	Manual, structured only	Automated, structured + unstructured
Threat detection	Limited to known risks	Can detect emerging risks via pattern recognition
Scalability & adaptability	Rigid	Dynamic, self-adjusting
Scenario simulation	Low, time-consuming	High, real-time generation

Figure 8 - Comparison of Traditional vs AI-enhanced ORM[32]

However, challenges remain regarding the data privacy concerns and risk of incorrect financial advice in the adoption of AI in ORM. Regarding an innovative solution to overcome such challenges, Generative AI enhances risk detection through pattern analysis of unstructured data, scenario generation and real-time dynamic risk monitoring. It also aids in designing effective mitigation strategies, automating labour-intensive tasks for efficiency and cost savings, and ensuring adaptability to evolving business and regulatory landscapes (Wang, 2023)[33]. When confronted with traditional ORM strategies that have inferior qualities due to their less effective detection of emerging threats and poor ability to handle vast data volumes, the capabilities of Generative AI are further highlighted as a powerful tool, which when integrated with effective and fluid strategies, have the inevitable ability of strengthening ORM practices (Wang, 2023).

1.1.3 AI-Powered Real-Time Monitoring and Decision-Making

In terms of real-time operational oversights, AI integrating with Internet of Things (IoT) sensors, cloud computing and big data analytics enables companies to have a continuously automated view of their operations. Observing its application in a case study

[31] Morgan Stanley (2023) *2023 ESG Report*
[32] Source: personal elaboration
[33] Wang, Y. (2023). *Generative AI in Operational Risk Management: Harnessing the Future of Finance*

on air pollution, the integration of Machine Learning (ML) algorithms and computational models to predict air quality index trends demonstrates significantly improved forecasting accuracy and enhanced real-time decision-making capabilities (Mani et al., 2021)[34]. This research studied systems like airborne-ground wireless sensor networks (WSNs) and UAV-based monitoring which collect and transmit real-time PM2.5 data, providing an up-to-date picture of air quality. These, paired with technologies to ensure precision of air quality predictions, help to anticipate future pollution levels (Mani et al., 2021). Ultimately, because of the reduced response time and more effective use of resources that proceeds because of AI-powered real-time monitoring, it advances capabilities in the field of decision-making. Drawing upon another industry, healthcare serves as another prime example of how the integration of AI and data analytics has enabled predictive insights that enhance clinical decisions through continuous patient monitoring. AI-driven healthcare trackers collect, evaluate, and interpret patient data to proactively manage medical conditions, ensuring early disease detection and improved patient outcomes (Snigdha, 2023)[35]. By leveraging wearable sensors, electronic health records (EHRs) and cloud computing, these systems provide real-time health updates, enabling medical professionals to make more informed and timely interventions. Furthermore, predictive modelling techniques support preventive treatment strategies, reducing hospital readmissions and optimising resource allocation (Snigdha, 2023). The success of AI in healthcare highlights its broader potential across industries, reinforcing its ability to drive efficiency, improve response times, and enhance overall decision-making processes.

Looking beyond air pollution and healthcare, we find that AI-powered real-time monitoring is also adopted in smart cities, industrial automation, logistics, and finance, where instantaneous data processing and ML algorithms enable organisations to make data-driven decisions in rapidly changing environments. The success of AI in these fields underscores its transformative potential across industries, reinforcing its ability to drive

[34] Mani, G., Viswanadhapalli, J.K. and Sriramalakshmi, P. (2021). AI powered IoT based Real-Time Air Pollution Monitoring and Forecasting. *Journal of Physics: Conference Series*
[35] Snigdha, E. Z., Hossain, M. R., & Mahabub, S. (2023). AI-Powered Healthcare Tracker Development: Advancing Real-Time Patient Monitoring and Predictive Analytics Through Data-Driven Intelligence

efficiency, improve response times, and enhance decision-making processes on a large scale.

Sector	AI Application	Outcome / Benefit
Environment	Air pollution prediction via WSNs and UAVs	Accurate forecasts, better resource response
Healthcare	Patient monitoring through wearables + EHR + ML	Early diagnosis, preventive treatments
Smart Cities	Infrastructure and traffic monitoring	Real-time service adjustment
Finance	Instant fraud detection, anomaly detection	Reduced losses, faster interventions
Logistics	Real-time fleet tracking, delivery optimization	Reduced delays, improved routing

Figure 9 - Sector-specific Applications of AI and their Operational Benefit[36]

1.1.4 AI-Driven Automation in Business Operations

Artificial Intelligence (AI)-driven automation is increasingly transforming business operations by enhancing efficiency, scalability, and adaptability across industries. As highlighted by Nayak et al. (2020)[37], AI technologies such as Machine Learning (ML), Natural Language Processing (NLP) and computer vision are being integrated into core operational workflows, streamlining decision-making processes and reducing human error in repetitive tasks. This integration is particularly impactful and constructs a greater competitive edge in areas like Supply Chain Management (SCM), customer service, and predictive maintenance, where data-driven insights can yield significant cost and time savings.

In industrial settings, AI-powered automation has redefined the traditional process flow: according to Waqar (2022)[38], industries leveraging AI technologies have reported improvements in operational efficiency of up to 40%, driven by predictive analytics,

[36] Source: personal elaboration
[37] Nayak, R., Nayyar, A., & Puri, V. (2020). *Smart Automated Systems Using Artificial Intelligence: A Review*
[38] Muhammad Waqar, Bhatti, I., Khan, A.H. and Lucas, M. (2024). AI-Powered Automation: Revolutionising Industrial Processes and Enhancing Operational Efficiency

intelligent monitoring, and real-time process optimisation. For example, in manufacturing, AI systems can automatically adjust machine parameters based on sensor data, leading to minimal downtime and enhanced product quality. The adoption of Robotic Process Automation (RPA), combined with AI, enables businesses to handle complex tasks such as invoice processing, compliance monitoring, and procurement more accurately and efficiently Nayak et al. (2020).

Nayak et al. (2020) also navigates the role of AI in enabling autonomous business decision-making through intelligent agents that continuously learn and adapt from new data inputs. These systems can detect anomalies, recommend corrective actions, and dynamically allocate resources based on real-time demand. This adaptability not only improves responsiveness but also enhances a company's ability to remain competitive in volatile markets. In practical terms, this means that AI agents can make complex operational decisions in real time, such as automatically adjusting inventory levels based on demand forecasts or optimise pricing strategies in response to market fluctuations. Unlike traditional rule-based systems, these agents evolve through reinforcement learning and feedback loops, becoming more accurate and efficient over time (Nayak et al., 2020).

One notable application of these AI agents is in the customer service sector where they handle thousands of inquiries simultaneously, offering personalised responses and leaving only nuanced or high-stakes issues to human agents. Another application is in the finance sector where these agents are employed for real-time fraud detection and credit risk assessment, autonomously flagging or blocking suspicious activities within milliseconds (Nayak et al., 2020). This offers financial companies a competitive advantage and a massively elevated service which enhanced customer protection and minimised financial losses. Furthermore, in strategic operations, intelligent agents contribute to scenario planning and risk management by simulating multiple future outcomes based on current and historical data, allowing businesses to make proactive, data-informed decisions with minimal human oversight (Waqar, 2022). A company's choice to decentralise their decision authority to intelligent agents enables them to have an accelerated response time, ultimately enabling businesses to operate with greater agility in fast-changing markets. Conclusively, these AI-driven autonomous systems empower organisations to be more responsive, resilient, and scalable, allowing leadership to focus on high-level strategic initiatives while routine and data-intensive decisions are handled at machine speed and accuracy.

Furthermore, AI-driven automation contributes to sustainable business practices by leveraging real-time data from IoT-enabled sensors to continuously monitor machinery performance, track energy consumption, and oversee material flows across the entire production process. Advanced ML algorithms analyse this data to detect patterns and anomalies that human operators might miss, for example, identifying when a particular machine consistently consumes more energy than expected under specific conditions or when material wastage exceeds normal thresholds. As Waqar (2022) points out, AI can significantly reduce energy consumption and waste in production lines by identifying inefficiencies and optimising input-output ratios. Moreover, the systems can dynamically adjust operational parameters, such as temperature, pressure, and processing speed, to maintain optimal efficiency without compromising product quality. Lastly, AI-powered systems support lean manufacturing principles by minimising overproduction, unnecessary transportation, and excessive inventory, all of which contribute to wasted energy and materials (Waqar, 2022). For example, in a smart factory environment, AI can balance production schedules based on real-time demand forecasts and resource availability, ensuring that production lines only run when necessary and with minimal excess.

Feature	Traditional Automation	AI-Driven Automation
Decision-making	Rule-based, static	Data-driven, adaptive, autonomous
Human intervention	Frequent	Minimal (exception-based)
Adaptability	Low	High, via machine learning and feedback
Sustainability monitoring	Absent or manual	Continuous, via real-time sensor integration
Cost-efficiency	Medium	High (thanks to predictive optimization)

Figure 10 - Differences between Traditional & AI-driven Automation[39]

In conclusion, the integration of AI into business operations is no longer a futuristic concept but a strategic imperative. It offers tangible benefits in terms of productivity, cost-effectiveness, and environmental impact. Looking into the future with the inevitable continuous growth of technology, businesses that sooner embrace AI-driven automation will gain a significant competitive edge.

1.1.5 Challenges and Barriers to AI Adoption

Despite its transformative potential, Artificial Intelligence (AI) adoption, like any new technology and revolution, comes with technical, organisational and ethical challenges. Bunte et al. (2021)[40] conducted a study and identified several key challenges hindering the adoption of AI in Small and Medium-sized Enterprise (SMEs). Those that stood out included a lack of expertise, high initial costs and inadequate infrastructure and resources. More importantly, the overall size of the company remained a limiting factor when confronted against giants in the market that benefit from economies of scale, advanced technological abilities, and wider access to capital. In their Survey, involving 411 individuals from 68 countries, they found that many employees were uncertain about the definition and application of AI in their production environments. This uncertainty

[39] Source: personal elaboration
[40] Bunte, A., Richter, F. and Diovisalvi, R. (2021). Why It is Hard to Find AI in SMEs: A Survey from the Practice and How to Promote It. *Proceedings of the 13th International Conference on Agents and Artificial Intelligence*

contributes to, and demonstrates, the lack of confidence amongst companies' workforce when implementing AI solutions (Bunte et al., 2021). The study also highlighted that the high initial costs and time investments required for AI implementation pose significant barriers for SMEs, which often operate with limited budgets and resources. Additionally, inadequate infrastructure, such as outdated equipment and insufficient data management systems, impede a seamless integration of AI technologies. The limited experience that employees within these companies have with AI further enlarged these challenges, as they may lack the necessary skills to effectively develop and maintain AI systems. Moreover, the smaller scale of SMEs means they may not have dedicated teams or departments to focus on AI initiatives, making it more difficult to prioritise and manage such projects (Bunte et al., 2021).

The hindering of the adoption of AI in SMEs has also been studied by Kumar et al. (2022)[41], exposing several critical barriers to its integration. The most noticeable challenge is the high implementation costs, which is most prohibitive for resource-constrained SMEs, and the shortage of skilled personnel capable of developing, deploying, and maintaining AI systems. Furthermore, poor data quality and the inherent complexity of AI technologies present significant technical challenges, particularly for organisations lacking robust digital infrastructure. Organisational factors such as cultural resistance, inadequate communication, and the absence of a clear and strategic roadmap for AI integration further exacerbate these issues. Collectively, these barriers highlight the need for structured support mechanisms, including targeted training, strategic planning, and improved data governance, to enable effective and sustainable AI adoption in the SME sector (Kumar & Bahl, 2022).

An unwavering challenge is overcoming organisational inertia which lies at the heart of digital business transformation. A case study on AsiaBank, a large traditional bank in Asia, examines how established firms address various forms of inertia during digital transformation (Kaganer, 2023)[42]. It identifies four key processes: embracing digital

[41] Kumar, A. and Bahl, R., 2022. *A study of barriers and benefits of Artificial Intelligence adoption in small and medium enterprise*

[42] Kaganer, E., Gregory, R. and Sarker, S. (2023). A Process for Managing Digital Transformation: An Organisational Inertia Perspective. *Journal of the Association for Information Systems*

computerisation, adopting digital business practices, enabling decentralised structures, and modernising IT architecture. The article sustains that together, these processes help to overcome psychological, cognitive, technical, political, and economic resistance. Generally within firms, overcoming organisational inertia is a critical challenge in the successful integration of AI, particularly for established or traditional enterprises. Resistance to change often stems from deeply rooted structures, legacy systems, risk-averse cultures, and a lack of digital readiness. To facilitate AI adoption, organisations must address their internal barriers, and promote a culture of innovation, upskilling employees, updating IT infrastructure, and aligning leadership around a clear AI strategy. Tackling these forms of inertia is essential for transforming operations and unlocking the full potential of AI-driven capabilities (Kaganer, 2023).

Barrier	Description
High implementation cost	Too expensive for resource-constrained SMEs
Lack of expertise	Shortage of skilled AI professionals
Poor data quality	Unstructured/incomplete data difficult to leverage
Infrastructure gaps	Outdated systems, no digital readiness
Organizational resistance	Cultural inertia, lack of clear AI strategy

Figure 11 - Key barriers to AI Adoption[43]

Lastly, there has been growing public concern about the ethical implications of integrating AI into business operations: UNESCO's *Recommendation on the Ethics of Artificial Intelligence* publication highlights the crucial importance of corporations' warnings and the global push for responsible AI use (UNESCO, 2023)[44]. In project management, the

[43] Source: personal elaboration
[44] UNESCO (2023). *Recommendation on the Ethics of Artificial Intelligence*

ethical dimension of AI is gaining prominence with survey results from the Project Management Institute (PMI) showing that 81% of professionals acknowledge its impact.

To better understand the ethical challenges that businesses are confronted with, a survey was conducted by Lasaite (2024)[45] focusing on AI use, ethical awareness, and digital practices in project environments. The findings, based on feedback from 66 participants and 55% of whom work in project settings, emphasise a significant gap in ethical preparedness. The results not only underscored the need for greater awareness of AI ethics and the leadership role project managers must play in addressing these dilemmas, but it also identified gender-related barriers and highlighted the need for inclusive, targeted educational initiatives to bridge this gap and promote ethical AI adoption across diverse demographics.

Ethical Concern	Source / Finding
Lack of ethical awareness	55% of project workers show gaps (Lasaite, 2024)
Gender-related disparities	Present in ethical education and engagement
Leadership in ethics	81% of professionals acknowledge ethical importance (PMI Survey)
Global call for responsibility	UNESCO's ethical AI framework for businesses

Figure 12 - Key Ethical Concerns in AI adoption and their Supporting Evidence[46]

1.1.6 The Future of AI in Operations

As Artificial Intelligence (AI) continues to advance, its already significant presence in business operations is projected to grow even more extensively. Rather than being limited to specific, isolated applications, AI is increasingly expected to become a foundational

[45] Lasaite, L. (2024). Ethical Considerations and Challenges of AI Adoption in Project Management. *Ethical Considerations and Challenges of AI Adoption in Project Management*
[46] Source: personal elaboration

element embedded throughout all levels of the organisation (McKinsey & Company, 2023)[47]. This integration will not only influence day-to-day decision-making processes but will also reshape operational models and play a central role in driving innovation, efficiency, and long-term value creation across the enterprise (Dogru & Keskin, 2020)[48].

One of the most promising developments is the expansion of hyper automation, which involves the integration of AI with Robotic Process Automation (RPA) and Machine Learning (ML) systems to automate not only routine tasks but also complex end-to-end business processes (Agrawal & Mitra, 2023)[49]. This is expected to reshape enterprise workflows, by allowing businesses to operate with minimal manual intervention while achieving higher levels of precision and accuracy in their outcomes.

Also, in the area of organisational design, AI is gaining traction: advanced AI tools are being developed to support workforce planning, helping companies assess current capabilities, forecast future talent needs, and improve hiring efficiency. AI also plays a growing role in employee engagement and retention, with ML models capable of analysing behavioural data to identify early signs of dissatisfaction or disengagement, thereby allowing HR departments to intervene proactively.

Sustainability, which is becoming an increasingly central focus for companies, is emerging as a critical pillar of corporate strategy. In this context, Artificial Intelligence is playing a vital role by providing essential support in achieving environmental objectives. By analysing energy consumption patterns and production metrics, AI systems can identify inefficiencies, optimise energy usage, and contribute to the reduction of emissions. These capabilities are especially valuable for organisations seeking to align with environmental regulations or work toward carbon neutrality targets. An example of AI-based predictive analytics being applied is in the energy and manufacturing sectors to lower consumption and improve resource efficiency (Mendelsohn, 2024)[50].

---

[47] McKinsey & Company, 2023, The state of AI in 2023: Generative AI's breakout year, McKinsey Report
[48] Dogru, A.K. and Keskin, B.B. (2020). AI in operations management: applications, challenges and opportunities. Journal of Data, Information and Management
[49] Dr. Ankush Agrawal and Mitra, A. (2023). SAP S/4HANA Supply Chain Planning and Manufacturing. BPB Publications
[50] Mendelsohn, S. (2024). AI will accelerate sustainability, but is no silver bullet. [online] World Economic Forum

While some projections have suggested that AI integration could lead to significant productivity improvements over the next decade, it is important to note that these vary by industry, implementation strategy, and technological maturity (ABA Journal, 2017)[51]. Rather than fixating on a single forecasted figure, it is more meaningful to recognise that businesses currently investing in AI technologies are already experiencing measurable improvements in process efficiency, cost savings, and operational flexibility, all of which is an early indication of AI's transformative potential across sectors (Deloitte, 2022)[52].

Area	AI Application	Expected Benefit
Operations	Hyperautomation (AI + RPA + ML)	Streamlined workflows, minimal human input
Human Resources	Workforce planning, engagement prediction	Better hiring, retention, proactive action
Sustainability	Energy usage analysis, emissions prediction	Cost saving, regulatory alignment
Strategy & Agility	Decision optimization, predictive modeling	Faster adaptation, competitive advantage

Figure 13 - AI Applications across Key Business Areas and their Expected Benefit[53]

According to Deloitte (2024), companies that fully embrace AI-driven operations can expect to see productivity gains of up to 50% by 2030, due to the reduction in inefficiencies, streamlining of workflows, and improvement in decision-making capabilities. This shift is set to reshape industries and redefine competitive advantages, favouring organisations that successfully integrate AI into their core business models and as a result, AI should not be viewed as simply an operational tool, but a critical driver of long-term business strategy and industry transformation (McKinsey & Company, 2023).

[51] Journal, A.B.A. (2017). JPMorgan Chase uses tech to save 360,000 hours of annual work by lawyers and loan officers. [online] ABA Journal
[52] Deloitte (2022). Predictive Maintenance and The Smart Factory. [online] Deloitte United States
[53] Source: personal elaboration

1.2 Fundamentals of AI Applied to Business Management

The integration of Artificial Intelligence (AI) into business management is fundamentally transforming the way that organisations make decisions, manage resources, and structure operations. AI technologies, especially those rooted in Machine Learning (ML), enable systems to process vast quantities of data in real-time, identify patterns, and make informed decisions without direct human intervention. These capabilities are allowing companies to move from reactive to predictive and even prescriptive decision-making models, enhancing responsiveness across supply chains, manufacturing, retail, and healthcare sectors (Weinzierl et al, 2024)[54].

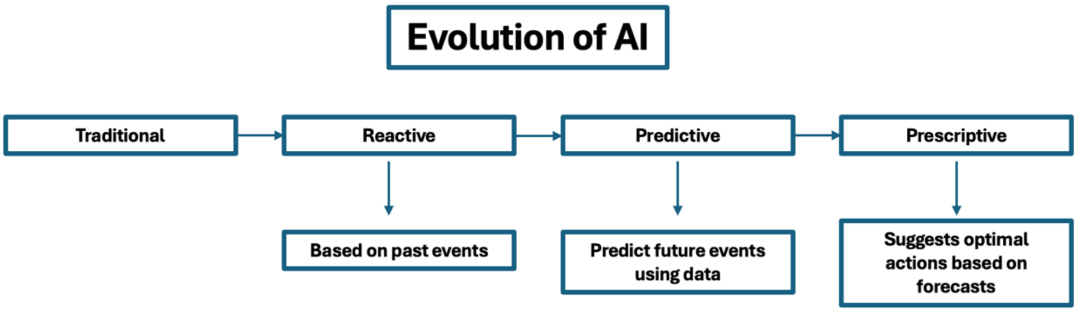

Figure 14 - Evolution of AI[55]

A study conducted by Dogru and Keskin (2020)[56] demonstrates that AI applications are now central to operational improvement in key sectors such as healthcare where ML models can assist in diagnostics and treatment personalisation. Additionally, manufacturing, where AI enhances production through predictive maintenance and smart automation, has seen significant efficiency gains, reduced downtime, and improved product quality as a result of these technologies. The use of AI in retail operations, including inventory management and customer behaviour analysis, allows companies to tailor supply chains and marketing efforts based on real-time consumer data (Dogru &

[54] Weinzierl, S., Zilker, S., Dunzer, S. and Matzner, M. (2024). Machine learning in business process management: A systematic literature review

[55] Source: personal elaboration

[56] Dogru, A.K. and Keskin, B.B. (2020). AI in operations management: applications, challenges and opportunities. Journal of Data, Information and Management

Keskin, 2020). These advances are not only improving efficiency, but they are reshaping how businesses define their competitive strategy.

Moreover, the implementation of Natural Language Processing (NLP) in customer service and organisational communication is automating interactions and streamlining service delivery. Explainable AI (XAI) is another essential pillar under the branch of artificial intelligence that focuses on rendering the decision-making processes of complex AI models transparent and understandable to human users (Leslie, 2020)[57]. This tool is becoming critical in ensuring that automated decisions, particularly those affecting consumers or regulated sectors, can be interpreted, and audited to maintain trust and legal compliance. The General Data Protection Regulation (GDPR), for instance, enforces the right of individuals to understand automated decisions affecting them, highlighting the growing importance of transparency in AI models.

Delving beyond the improvements that AI brings to technical efficiency, we also witness its influence in corporate governance and organisational design. This is mainly because the automation of operational tasks prompts the need to reallocate human labour towards higher-value activities. As noted in the same study, this shift can lead to both displacement and reinstatement effects in the workforce, displacing certain roles while creating new ones that focus on training, monitoring, and explaining AI systems (Dogru & Keskin, 2020) .

In this evolving landscape, AI is not just a technological upgrade, but a foundational enabler of business transformation, whereby its adoption requires interdisciplinary collaboration, regulatory adaptation, and a rethinking of strategic planning.

1.2.1 Machine Learning: The Core of AI in Business Management

Machine Learning (ML) represents a central pillar in AI-driven business transformation, enabling systems to learn from data patterns and improve performance over time without the need for explicit programming. In the context of business management, ML plays a key role in supporting data-driven decision-making. These algorithms are trained on large historical and real-time datasets which are able to identify trends, detect correlations,

[57] Leslie, D. (2020). Explaining Decisions Made with AI. SSRN Electronic Journal

and provide actionable insights that enhance planning and strategic execution (Shinde & Shah, 2018)[58].

This analytical power allows organisations to better anticipate market dynamics, optimise product development, and refine customer engagement strategies. In particular, ML is extensively applied in areas such as demand forecasting, inventory optimisation, and sentiment analysis, where the ability to extract and process hidden patterns from complex data provides a competitive advantage for businesses (Choi, Wallace & Wang, 2018)[59].

One of the most impactful applications of ML is in customer analytics. By analysing purchasing histories, browsing behaviour, and engagement data, ML models allow companies to personalise recommendations, improve marketing efficiency, and enhance customer relationship management, which in turn increase customer satisfaction and loyalty (Alanne et al., 2019)[60].

ML also supports numerous applications in finance, including algorithmic trading, fraud detection, credit risk assessment, and portfolio optimization. By processing large and complex datasets, ML models can uncover patterns and make predictions that enhance decision-making and operational efficiency. For instance, ML-driven credit scoring systems have shown improved accuracy over traditional models by incorporating alternative data sources (Khandani, Kim, & Lo, 2010)[61]. As a result, financial institutions increasingly rely on ML to gain a competitive edge and manage risk more effectively.

Alternatively, when drawing into the manufacturing sector we find that ML also brings benefits through predictive maintenance systems that process real-time sensor data from industrial equipment. These systems detect early signs of mechanical stress or

---

[58] Shinde, P.P. and Shah, S. (2018). A Review of Machine Learning and Deep Learning Applications

[59] Choi, T.-M., Wallace, S.W. and Wang, Y. (2018). Big Data Analytics in Operations Management. Production and Operations Management

[60] Alanne, K. and Sierla, S. (2022). An overview of machine learning applications for smart buildings. Sustainable Cities and Society

[61] Khandani, A.E., Kim, A.J. and Lo, A.W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance

failure, allowing for maintenance interventions before breakdowns occur, reducing downtime, lowering costs, and extending asset life cycles (Zonta et al., 2020)[62].

Another advanced application is in dynamic pricing where ML algorithms continuously analyse market demand, competitor pricing, and economic signals to automatically adjust prices in real time. This allows businesses to remain competitive whilst maximising their revenue across varying market conditions.

Business Function	ML Application	Benefits	Techniques Commonly Used
Marketing & CRM	Recommendation engines, sentiment analysis	Personalisation, customer loyalty	Neural Networks, Clustering
Finance	Credit scoring, fraud detection	Risk reduction, faster decision-making	Ensemble models, SVM
Manufacturing	Predictive maintenance	Lower downtime, cost savings, longer equipment life	Decision Trees, Time Series Models
Sales / Pricing	Dynamic pricing	Revenue maximisation, competitiveness	Regression, Reinforcement Learning
Operations Planning	Demand forecasting, inventory management	Efficiency, waste reduction	Regression, Ensemble Methods

Figure 15 - Key Business Applications of Machine Learning: Functions, Benefits, and Techniques[63]

A wide range of ML techniques, such as support vector machines, decision trees, artificial neural networks, and ensemble methods, are employed across industries to solve

[62] Zonta, T., da Costa, C.A., da Rosa Righi, R., de Lima, M.J., da Trindade, E.S. and Li, G.P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. Computers & Industrial Engineering

[63] Source: personal elaboration

classification, clustering, and regression tasks. These models form the backbone of advanced business intelligence systems, which help organisations to monitor performance indicators, detect emerging trends, and adjust their strategic direction with greater agility.

By integrating ML into their decision-support frameworks, businesses are able to move toward predictive and prescriptive models that not only describe what has happened but also anticipate what is likely to happen next. To conclude, it appears evident that as AI continues to evolve, ML remains essential in enabling smarter, faster, and more adaptive operations across sectors (Shinde & Shah, 2018).

1.2.2 Natural Language Processing (NLP) and AI-Driven Communication

Natural Language Processing (NLP) is a subfield of Artificial Intelligence (AI) that focuses on enabling machines to understand, interpret, generate, and respond to human language in a contextually meaningful way. By integrating principles from linguistics, Machine Learning (ML), and Deep Learning (DL), NLP facilitates the efficient processing and analysis of large volumes of unstructured natural language data, thereby enhancing human-computer interaction across various applications (Cambria & White, 2014)[64].

NLP has become integral to modern business management, offering diverse applications that enhance operational efficiency and customer engagement. One prominent application is AI-powered customer service, where virtual assistants and chatbots utilise NLP to understand and respond to customer inquiries, providing instant support and reducing the workload on human agents (Cai, 2025)[65].

Another significant application of Natural Language Processing (NLP) is sentiment analysis, which focuses on examining customer feedback, reviews, and social media content to assess public opinion toward products, services, or brands. By analysing this unstructured text data, organisations can better understand customer satisfaction, detect trends, and identify areas for improvement. This technique has proven valuable for

[64] Cambria, E. and White, B. (2014). Jumping NLP Curves: A Review of Natural Language Processing Research [Review Article]. IEEE Computational Intelligence Magazine

[65] Cai, K. (2025). Verizon says Google AI for customer service agents has led to sales jump.

real-time reputation management and strategic decision-making (Medhat, Hassan, & Korashy, 2014)[66].

Additionally, NLP facilitates automated document processing by extracting relevant information from unstructured text data, such as customer reviews, social media posts, and news articles. This capability enhances data analysis by identifying patterns, trends, and sentiments that are not immediately obvious in large datasets, thereby improving efficiency and accuracy in handling large volumes of textual information (Docdigitizer, 2023)[67].

Application	Description	Benefits
Customer Service Automation	Chatbots and virtual assistants for real-time support	Reduced workload, faster response, customer loyalty
Sentiment Analysis	Text analysis of reviews/social media to extract emotions/opinions	Reputation monitoring, product feedback
Document Processing Automation	Extracting structured info from unstructured text	Time-saving, accuracy in repetitive tasks

Figure 16 - NPL: Applications and Benefits[68]

In conclusion, NLP plays a crucial role in advancing AI-driven communication by enabling machines to interact with human language in a meaningful and efficient way. By combining insights from linguistics, ML, and DL, NLP empowers businesses to process and analyse vast amounts of unstructured text data (Cambria & White, 2014). Its applications, ranging from AI-powered customer service to sentiment analysis and automated document processing, significantly enhance operational efficiency, customer engagement, and strategic decision-making. As organisations increasingly rely on real-time data and digital interactions, NLP stands as a foundational technology driving more intelligent, responsive, and effective communication systems.

[66] Medhat, W., Hassan, A. and Korashy, H. (2014). Sentiment Analysis Algorithms and applications: a Survey. Ain Shams Engineering Journal

[67] Docdigitizer. (2023). Natural Language Processing (NLP) for Document Understanding: Extracting Meaning and Context from Textual Content - Docdigitizer

[68] Source: personal elaboration

1.2.3 Explainable AI (XAI) and Ethical Business Management

As Artificial Intelligence (AI) systems grow in complexity and are increasingly integrated into high-stakes decision-making processes, the need for clarity and accountability becomes paramount. Explainable Artificial Intelligence (XAI) emerges as a crucial framework aimed at demystifying the internal workings of AI models by providing transparent and human-understandable explanations for their outputs. This interpretability is essential for identifying and mitigating potential biases, ensuring fairness, and allowing stakeholders to trust the system's recommendations. In sectors like hiring, finance, and healthcare, where algorithmic decisions can significantly impact individuals and society, XAI not only builds user confidence but also helps organisations adhere to ethical standards and legal requirements, such as those surrounding fairness, discrimination, and data protection regulations (European Commission, 2023)[69].

In addition, talent acquisition and workforce management increasingly rely on XAI to support ethical business practices by ensuring transparency, fairness, and accountability in human resource decisions. XAI enables recruiters and HR professionals to understand how AI models evaluate resumes, screen candidates, or predict employee performance, thereby reducing the risk of hidden biases and discrimination in the hiring process. By providing clear, interpretable reasoning behind decisions, XAI allows organisations to justify selections, foster inclusivity, and build trust with applicants. Moreover, it supports compliance with equal opportunity regulations and ethical standards, making it a vital tool for responsible and equitable workforce management in the age of AI (Cappelli, P., Tambe, P. and Yakubovich, V. 2019)[70]. However, if the training data contains bias, AI models may unintentionally favour certain demographic groups, leading to discrimination. Ensuring interpretability in these systems allows companies to identify and correct potential bias, promoting fairness in hiring practices (Harvard Business Review, 2024).

---

[69] European Commission (2023). A European approach to Artificial intelligence | Shaping Europe’s digital future

[70] Cappelli, P., Tambe, P. and Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. SSRN Electronic Journal

The integration of XAI into the financial sector has become increasingly vital, particularly in areas such as lending and credit scoring, where machine learning (ML) algorithms are used to evaluate applicants' creditworthiness (Deloitte Insights, 2024)[71]. Traditional black-box models, while powerful, often lack the transparency necessary to ensure ethical decision-making. This opacity can lead to unintended consequences, such as biased outcomes that disproportionately disadvantage specific demographic groups, thereby reinforcing existing socio-economic inequalities. XAI addresses these challenges by making the decision-making process of AI systems more transparent and interpretable, allowing financial institutions to understand and justify the basis of each decision. This level of openness is essential not only for fostering consumer trust but also for aligning with ethical standards and regulatory demands (PwC, 2023)[72]. The European Commission's article on the European approach to artificial intelligence underscores the EU's commitment to fostering AI that is both innovative and aligned with ethical standards. Central to this approach is the emphasis on "excellence and trust," aiming to boost research and industrial capacity while ensuring safety and fundamental rights (European Commission, 2023). Therefore, by promoting XAI the EU seeks to ensure that AI systems in the financial sector are interpretable and free from bias, thereby supporting ethical business management and maintaining public trust.

In the healthcare sector, XAI has emerged as a critical component in advancing ethical business management, particularly as AI-driven systems become increasingly integrated into clinical decision-making processes. These systems are employed in diverse applications, including diagnostic support, treatment planning, and patient risk stratification. However, the opacity of many advanced ML models presents significant ethical concerns, especially in contexts where decisions can directly impact patient outcomes. XAI addresses these concerns by offering interpretable and transparent insights into how AI models arrive at specific conclusions, thereby facilitating clinical accountability, informed consent, and shared decision-making between medical professionals and patients. This transparency not only improves trust in AI-assisted

[71] Deloitte Insights, 2024, AI-Driven Process Automation: Unlocking Enterprise Efficiency, Deloitte Review
[72] PwC, 2023, AI's $15.7 Trillion Impact on the Global Economy, PwC AI Report

healthcare but also aligns with regulatory and ethical requirements for fairness, non-discrimination, and patient autonomy. As highlighted by Holzinger et al. (2017)[73], the implementation of explainable systems is essential for ensuring that AI in healthcare remains human-centred and ethically sound, enabling stakeholders to validate and audit decisions effectively.

Despite the numerous advantages offered by XAI, its implementation within business operations is not without significant challenges (McKinsey & Company, 2023)[74]. One of the foremost concerns is algorithmic bias, wherein AI models trained on historically biased or unrepresentative datasets may reinforce or even exacerbate existing social and economic inequities. This poses ethical and reputational risks for organisations, particularly in high-stakes domains such as finance, healthcare, and employment. As a result, businesses must establish robust mechanisms for the continuous monitoring, auditing, and refinement of AI systems to ensure fairness and mitigate discriminatory outcomes. Additionally, the evolving regulatory landscape presents further complexity. Legislative frameworks such as the General Data Protection Regulation (GDPR), the EU Artificial Intelligence Act, and the California Consumer Privacy Act (CCPA) mandate heightened levels of transparency, accountability, and data protection in AI deployment (European Commission, 2024). Ensuring compliance with these regulations requires organisations to embed transparency into the design and governance of AI systems, underscoring the intersection between ethical responsibility and legal obligation in contemporary AI management.

In addition, XAI governance plays a critical role in aligning AI-driven decisions with business ethics and corporate values. Business leaders must ensure that AI applications support organisational goals while adhering to ethical standards, avoiding reputational damage, and maintaining consumer trust (McKinsey & Company, 2024).

As XAI continues to shape industries, organisations must balance technological advancements with ethical responsibility. Investing in explainable AI frameworks will be

[73] Holzinger, A., Langs, G., Denk, H., Zatloukal, K. and Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. WIREs Data Mining and Knowledge Discovery

[74] McKinsey & Company, 2023, The state of AI in 2023: Generative AI's breakout year, McKinsey Report

critical to maintaining compliance, ensuring fairness, and fostering trust in AI-driven decision-making.

1.3 Generative AI and Digital Twins

In recent years, Artificial Intelligence (AI) has undergone a substantial evolution, expanding beyond traditional automation and predictive analytics to encompass advanced generative and simulation-based technologies. This progression is exemplified by the emergence of Generative AI and Digital Twin technologies, both of which are fundamentally reshaping how organizations innovate, manage operations, and make strategic, data-driven decisions. These technologies embody a new class of AI systems capable not only of interpreting data but also of creating content and simulating real-world complexities.

Aspect	Generative AI	Digital Twins
Core Function	Generates original content (text, image, code)	Simulates real-world systems dynamically
Key Technologies	Deep learning, transformer models	IoT, machine learning, simulation engines
Output	Synthetic data, language, software, design concepts	Real-time virtual representations of physical entities
Use Cases	Report generation, chatbot response, code suggestion	Predictive maintenance, scenario simulation, resource optimization
Shared Foundations	ML models, data integration, real-time analytics	ML models, data integration, real-time analytics
Synergy	Automates scenario creation in digital twins	Uses GenAI to generate or test content within simulated environments

Figure 17- An Overview of Generative AI and Digital Twin Technologies[75]

[75] Source: personal elaboration

Generative AI distinguishes itself through its capacity for strong emergence, generative novelty, and systemic outputs. These properties allow it to autonomously produce coherent and contextually appropriate content such as text, images, or code (Storey et al., 2025)[76]. As a "meta-information technology," Generative AI supports a wide array of organizational functions, from report writing and software development to automating content production and enhancing human–computer interaction (Storey et al., 2025). Meanwhile, Digital Twins leverage real-time data from IoT sensors, integrated with Machine Learning (ML) and simulation engines, to create dynamic, high-fidelity virtual models of physical entities and systems. These models allow businesses to test scenarios, predict failures, and optimize performance without impacting real-world operations (Alanne et al., 2023)[77].

Although distinct in their core functions, Generative AI and Digital Twins are synergistically interconnected through shared reliance on advanced computational models, data-driven learning, and real-time analytics. Their integration is increasingly driving intelligent automation, personalized services, and resilient infrastructure across sectors including manufacturing, healthcare, logistics, and urban planning (Alanne et al., 2023; Storey et al., 2025[78]).

This section will delve into the core mechanisms of Generative AI and Digital Twins, but more specifically their technological underpinnings, business applications, and transformative potential. It also explores how their convergence is accelerating the shift toward intelligent automation, personalized services, and resilient infrastructure, marking a new era of AI-driven transformation in business operations.

[76] Storey, V.C., Yue, W.T., Zhao, J.L. and Lukyanenko, R. (2025). Generative Artificial Intelligence: Evolving Technology, Growing Societal Impact, and Opportunities for Information Systems Research. Information Systems Frontiers
[77] Alanne, K. and Sierla, S. (2022). An overview of machine learning applications for smart buildings. Sustainable Cities and Society
[78] Storey, V.C., Yue, W.T., Zhao, J.L. and Lukyanenko, R. (2025). Generative Artificial Intelligence: Evolving Technology, Growing Societal Impact, and Opportunities for Information Systems Research. Information Systems Frontiers

1.3.1 Generative AI: Transforming Content Creation and Automation

Generative Artificial Intelligence (AI) built on advanced Deep Learning (DL) architectures, particularly transformer models, has emerged as a revolutionary paradigm in content creation and automation, enabling machines to autonomously generate text, images, music, programming code, and other novel data with impressive realism and fidelity (Pandy, 2024[79]; Mandvikar, 2023)[80]. Unlike traditional AI systems focused on analysis or prediction, generative models, such as Generative Adversarial Networks (GAN), specialize in synthesizing entirely new content that mimics human creativity (Pandy, 2024). This technological foundation has broadened the scope of automation from routine tasks to creative and cognitive processes, yielding unprecedented efficiency and scalability in various applications (Mandvikar, 2023). To learn how to create new output, these models analyse existing content structures, adapt to different tones and styles, and ensure that the generated material remains relevant to specific audiences.

For instance, in digital marketing and branding, generative AI tools can instantly produce high-quality marketing copy, logos, and personalized advertisements, fundamentally changing how brands engage customers through highly tailored content (Emerald Publishing, 2024)[81].

Likewise, in customer service, organizations are deploying conversational AI agents powered by Large Language Models (LLM) to handle complex inquiries with human-like responsiveness, thereby automating customer engagement and support with consistent quality (Emerald Publishing, 2024; Pandy, 2024). The aim here is to ultimately improve customer interactions through AI-powered chatbots and advanced virtual assistants. Unlike rules-based chatbots that rely on pre-written responses, generative AI enables more natural, dynamic, and context-aware conversations by continuously learning from interactions, improving their ability to understand and answer complex questions. Businesses integrate AI-driven virtual assistants to handle customer service inquiries,

[79] Pandy, G. (2024). Generative AI: Transforming the Landscape of Creativity and Automation. ResearchGate
[80] Mandvikar, S. (2023). Process Automation 2.0 with Generative AI Framework. ResearchGate
[81] Emerald Publishing. (2024). The evolving role of generative AI in digital marketing and branding. Journal of Consumer Marketing

reducing wait times and freeing human agents to focus on more complex issues, ultimately improving overall customer satisfaction, reducing cost and processing time.

Generative AI is also being leveraged in software development, as code generation models assist developers by drafting and debugging code, which accelerates development cycles and reduces human error in the engineering process (Mandvikar, 2023; Pandy, 2024). AI models trained on vast repositories of programming languages can write functional code snippets, suggest improvements, and even identify potential vulnerabilities in existing codebases. Also in this case, capability enhances developer productivity by reducing repetitive tasks, streamlining workflows, and enabling engineers to focus on higher-level problem-solving rather than manual coding.

In addition, these models can create synthetic data for training and simulations, alleviating data scarcity and privacy challenges by generating realistic datasets where real data are limited or sensitive (Pandy, 2024). In fields where data privacy and security are paramount, such as healthcare and finance, AI models generate artificial datasets that retain the statistical properties of real-world data without exposing sensitive information, making it possible for businesses to train ML models while complying with strict data protection regulations.

Strategically, the integration of generative AI across sectors unlocks new opportunities for innovation and personalization, enabling businesses to craft creative solutions and customized experiences at scale, while operationally it streamlines content workflows and decision-making processes, leading to significant gains in productivity and efficiency (Emerald Publishing, 2024; Mandvikar, 2023).

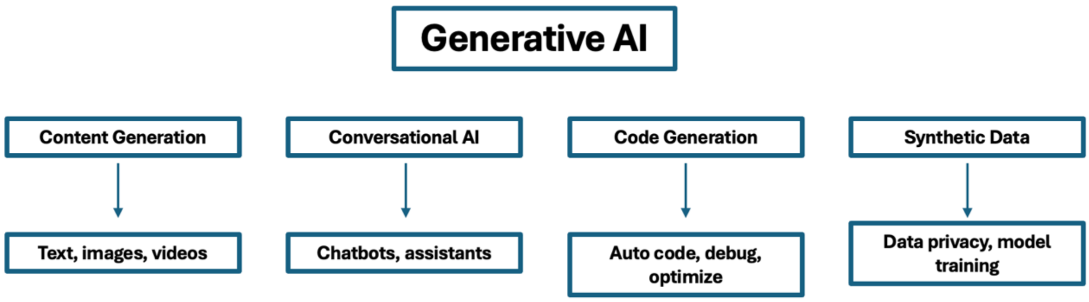

Figure 18 - Core Applications of Generative AI in Business Operations[82]

In sum, generative AI's advancement represents a paradigm shift in both strategy and operations, as it reshapes creative practices, automates complex tasks, and drives value creation across diverse industries.

1.3.2 Digital Twins: Virtual Models for Real-World Optimisation

Digital twins are virtual replicas of physical objects, processes, or systems in high fidelity, allowing businesses to monitor, analyse, and optimise real-time operations. They integrate Internet of Things (IoT) sensor data, Machine Learning (ML) algorithms, and sophisticated analytics, which are continuously updating to reflect the real behaviour of the physical entities. By simulating real conditions, digital twins allow businesses to test scenarios, anticipate potential failures, and implement improvements without impacting real operations (Crespi et al, 2023)[83].

One of the largest applications of this technology is within manufacturing, where they assist in optimising the efficiency of manufacturing and reducing operational costs. With the monitoring and analysis of sensor data on machinery within the industrial environment, digital twins provide producers with real-time data on machinery performance. Ultimately this data enables swift detection of inefficiencies and provides predictive maintenance expectations before breakdowns take place, expanding the machinery's lifespan and improving the overall output (Camarella et al, 2024)[84] .

Aside from the manufacturing industry, digital twins are also transforming supply chain and logistics management. With a virtual copy of supply chain operations in real time, organisations can analyse operational bottlenecks, investigate potential disruptions, and dynamically alter shipping routes and inventory levels. AI-powered simulations allow

[82] Source: personal elaboration
[83] Crespi, N., Drobot, A. and Minerva, R. (2023). The Digital Twin: What and Why?
[84] Camarella, S., Conway, M., Goering, K., Huntington, M. (2024). Transforming Digital twins: The next frontier of factory optimization | McKinsey

organisations to test multiple supply chain scenarios, optimising resource allocation and reducing inefficiency (Rathore et al., 2021)[85].

The healthcare industry is also being impacted positively by integrating digital twin technology, particularly in treatment planning and personalising medicine. Through the development of virtual representations of patients, medical practitioners are capable of predicting the outcome of treatment, individualising drug dosages, and predicting the course of the disease. Digital twins of human organs are being utilised to try out novel surgical procedures and develop personalised treatment regimens, which eventually enable interventions to be more precise and effective (Rathore et al., 2021). The technology's most valuable application to the sector is within the critical care division and the management of chronic conditions, where predictive modelling and early intervention significantly improve the patient's outcome.

In urban planning and infrastructure management, digital twins are being utilised to optimise city efficiency, traffic, and energy consumption. Through AI-powered analytics, urban planners can foresee different urban planning scenarios and make informed choices on how to develop sustainably. These results have already been visible in cities such as Singapore and London which have already adopted digital twin technology to enhance transportation networks, reduce their environmental impact, and enhance their emergency response (Crespi et al, 2023).

Layer	Function
IoT / Sensors	Feed real-time data into the virtual model
Machine Learning	Analyze patterns, detect anomalies, predict scenarios
Simulation Engine	Emulates operations and tests "what-if" scenarios

Figure 19 - Core Technological Layers of a Digital Twin[86]

Despite its advantages, widespread use of digital twin technology is held back by several challenges such as the complexity of integrating mass data. Moreover, it holds high

[85] Mazhar Rathore, M., Shah, S.A., Shukla, D., Bentafat, E. and Bakiras, S. (2021). The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities.
[86] Source: personal elaboration

investment costs and requires advanced cybersecurity to protect digital twins, all of which are significant barriers. However, with the continued development of AI, cloud computing, and IoT connectivity, the capabilities of digital twins will grow, and they will become increasingly important and powerful tools to boost efficiency, reduce costs, and support innovation (Feuerriegel et al., 2023[87]; Rathore et al., 2021).

1.4 AI Applications for Real-Time Decision-Making and Process Optimisation

Artificial Intelligence (AI) is transforming business operations by enabling real-time decision-making, process optimisation, and dynamic resource allocation. Unlike traditional data analysis methods that rely on historical data, AI-driven systems continuously process and analyse real-time information to detect patterns, predict outcomes, and automate adjustments.

This section will explore how AI enhances business agility, operational efficiency, and process automation, with a focus on real-time analytics, hyper automation, and AI-driven sustainability initiatives.

1.4.1 AI for Real-Time Decision-Making

Across various industries, Artificial Intelligence (AI) has become integral to real-time decision-making, enabling organisations to process vast amounts of data swiftly and accurately, enhancing operational efficiency, reduces risks, and improves customer experiences.

In the financial sector, it is increasingly deployed to enhance decision-making speed, process optimisation, and security. AI-driven algorithms are capable of analysing vast volumes of global financial data in real time, enabling institutions to execute high-frequency trades within milliseconds in response to market fluctuations (DigitalDefynd, 2024)[88]. This capability not only provides a competitive advantage but also contributes to the growing adoption of AI across a range of financial applications. A significant area of impact is fraud detection, where AI systems employ anomaly detection techniques to

[87] Feuerriegel, S., Hartmann, J., Janiesch, C. and Zschech, P. (2023). Generative AI. Business & Information Systems Engineering

[88] Team DigitalDefynd (2024). 5 ways JP Morgan is using AI - Case Study [2024]. DigitalDefynd

identify irregular transaction patterns, thereby mitigating risk and enhancing asset protection. This, in turn, plays a critical role in maintaining and strengthening customer trust. For instance, JPMorgan implemented AI-powered fraud detection and risk management solutions in 2023 to address the increasing complexity of financial threats (DigitalDefynd, 2024). These systems enabled the institution to proactively identify potential risks and reduce false positives, thereby improving the overall effectiveness of its fraud prevention strategies. This case exemplifies how AI can drive transformative improvements in financial oversight and customer assurance (J.P. Morgan, 2023)[89].

It has also found its applicability in retail and e-commerce, where AI systems dynamically adjust product pricing and manage inventory based on real-time demand fluctuations. By analysing customer behaviour and market trends, AI enables personalised shopping experiences and optimises stock levels, reducing overstock situations and minimising shortages, also increasing sales and customer satisfaction, as well as improving overall performance (Basal et al, 2024)[90].

Instead, manufacturing industries utilise AI to monitor production lines continuously, detecting defects and adjusting machine settings automatically, resultantly minimising downtime and maintaining product quality. AI-powered predictive maintenance systems analyse equipment data to foresee potential failures, allowing for timely interventions that extend machinery lifespan and enhanced operational efficiency (Amin, 2025)[91].

Within the healthcare industry, AI-driven monitoring systems analyse patient vital signs in real-time, alerting medical professionals to anomalies that may require immediate attention. This continuous monitoring facilitates prompt interventions, improving patient outcomes. AI also assists in diagnostics by interpreting medical images and patient data, leading to more accurate and timely diagnoses.

1.4.2 AI and Hyper automation in Business Operations

[89] J.P. Morgan (2023). AI Boosting Payments Efficiency & Cutting Fraud | J.P. Morgan

[90] Basal, M., Saraç, E. and Özer, K. (2024). Dynamic Pricing Strategies Using Artificial Intelligence Algorithm. Open Journal of Applied Sciences

[91] Amin, I. (2025). AlphaBOLD. [online] Microsoft Dynamics and NetSuite Partner & Dynamics CRM Consultants in San Diego

Hyper automation represents a significant advancement in digital transformation, leveraging cutting-edge technologies such as Robotic Process Automation (RPA), Machine Learning (ML), and Artificial Intelligence to automate intricate business operations (Haleem et al., 2021)[92]. Unlike traditional automation, which focuses on repetitive and rule-based tasks, hyper automation extends its capabilities to processes that previously required human expertise. By integrating AI-driven decision-making with RPA, organisations can automate complex workflows, dynamically identify optimisation opportunities, and enhance overall operational efficiency (Haleem et al., 2021).

This approach enables businesses to streamline virtual tasks that were traditionally handled by employees, allowing for a more seamless integration between automated systems and human expertise. Through the combination of AI, data analytics, and automation tools, hyper automation not only reduces manual effort, but also enhances adaptability, enabling organisations to meet evolving business demands with greater precision. By incorporating business intelligence systems and predictive analytics, companies can gain deeper insights, optimise resource allocation, and improve decision-making processes (Haleem et al., 2021).

The implementation of hyper automation fosters greater agility, allowing organisations to respond proactively to market fluctuations, operational challenges, and customer needs. As businesses continue to embrace this transformation, the synergy between AI-driven automation and human expertise will redefine efficiency, scalability, and innovation in various industries.

Looking at the finance sector, hyper automation facilitates the automation of intricate processes such as expense management, compliance reporting, and invoice processing (Needhi, 2024)[93]. AI algorithms extract and analyse data from financial documents, ensuring accuracy, detecting anomalies, and expediting financial workflows. Ultimately, this leads to more efficient operations, reducing manual errors, and enhancing decision-making capabilities(Needhi, 2024).

[92] Haleem, A., Javaid, M., Singh, R.P., Rab, S. and Suman, R. (2021). Hyperautomation for the enhancement of automation in industries. Sensors International

[93] Jeyadev Needhi (2024). How AI Transformed Financial Fraud Detection: A Case Study of JP Morgan Chase

Manufacturing industries leverage hyper automation by integrating AI-controlled robotic systems capable of self-adjustment based on real-time performance metrics. Permitting the automation of complex tasks, continuous monitoring of equipment, and predictive maintenance, thereby enhancing production efficiency and product quality (Haleem et al., 2021).

Aspect	Traditional Automation	Hyperautomation
Scope	Repetitive, rule-based tasks	Complex, cognitive workflows
Intelligence	Rule engines	AI/ML-driven decision-making
Adaptability	Static	Dynamic, real-time response
Tech stack	Single tools (e.g. RPA)	Integrated AI, RPA, analytics, orchestration

Figure 20- Traditional and Hyper automation[94]

1.4.3 AI for Process Optimisation and Resource Efficiency

Artificial Intelligence (AI) is playing a transformative role in optimising business processes and promoting sustainable practices across industries. By leveraging AI, organisations can enhance efficiency, allocate resources dynamically, and significantly reduce waste, leading to cost savings and improved environmental outcomes. The ability of AI to analyse vast datasets, predict trends, and automate decision-making has made it an indispensable tool for companies aiming to improve both operational performance and sustainability.

AI-driven optimisation is particularly evident in industries where complex processes and resource-intensive operations require continuous monitoring and adjustments. Exemplary sectors are both energy and manufacturing, where AI systems analyse real-time data from sensors and production lines to detect inefficiencies, adjust operational parameters, and predict maintenance needs before disruptions occur, but also react instantly in order to adjust output production based on the analysed data at each instant. This proactive approach prevents costly downtime, extends the lifespan of machinery, and reduces excessive energy consumption.

[94] Source: personal elaboration

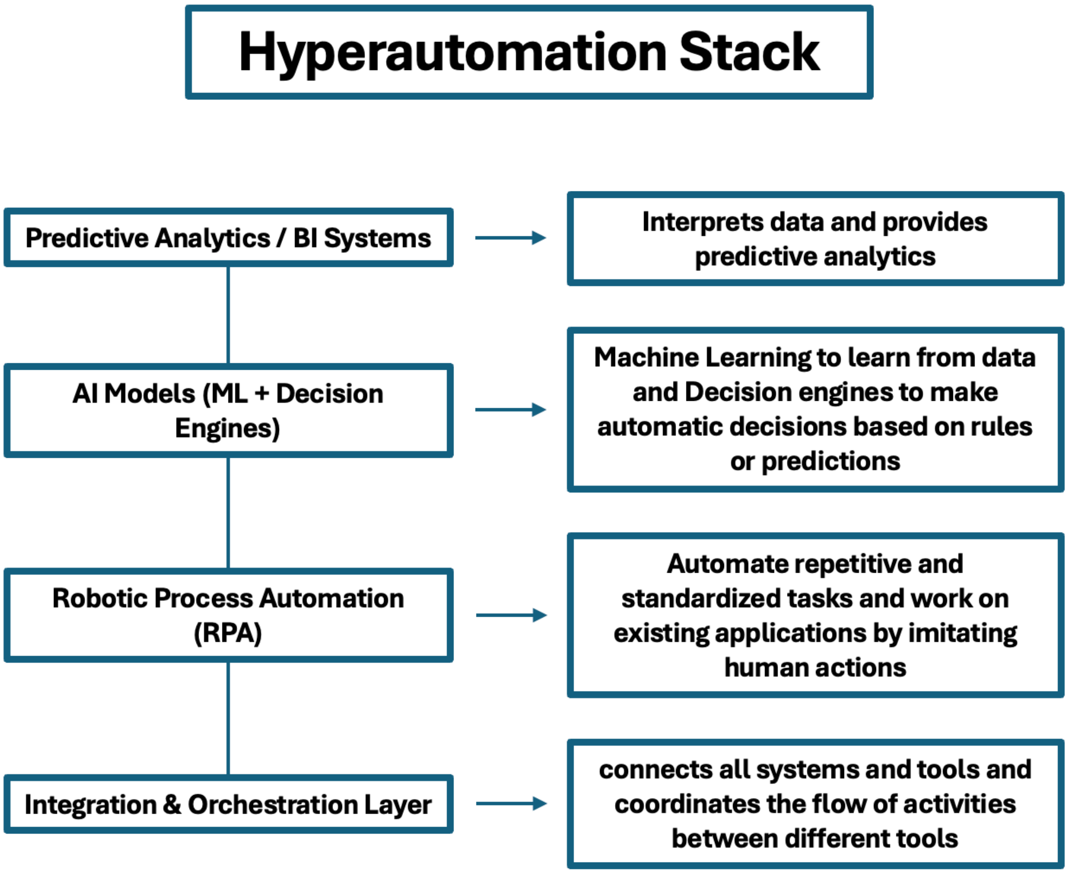

Figure 21 - Architecture of the Hyperautomation Technology Stack[95]

Similarly, in financial services AI streamlines operations by automating coding and data analysis tasks, allowing human resources to be reallocated to more strategic initiatives (Nuti et al., 2011)[96], thereby improving the overall productivity. In the same sector, the use of AI in algorithmic trading in this sector, which refers to "the use of computer programs to automate one or more stages of the trading process", is becoming increasingly widespread (Cohen, 2022)[97]. This is because these systems have significant advantages over human traders by processing vast and diverse datasets almost instantaneously. Also, their ability to execute high-frequency trading allows them to detect and capitalise on market inefficiencies and short-term price fluctuations far more quickly and accurately than human operators (Cohen, 2022).

[95] Source: personal elaboration
[96] Nuti, G., Mirghaemi, M., Treleaven, P. and Yingsaeree, C. (2011). Algorithmic Trading. Computer
[97] Cohen, G. (2022). Algorithmic Trading and Financial Forecasting Using Advanced Artificial Intelligence Methodologies. Mathematics

Beyond enhancing business efficiency, AI is driving significant advancements in sustainability: AI-powered energy management systems optimise electricity distribution by analysing consumption patterns and adjusting supply; accordingly, this is aiding to minimise waste and lower carbon emissions. Companies in the renewable energy sector are utilising AI to enhance wind and solar power efficiency by predicting weather conditions and adjusting energy outputs dynamically (Haleem et al., 2021)[98]. The integration of AI in agriculture has also contributed to more sustainable farming practices, with AI algorithms analysing soil health, predicting crop yields, and identifying pest infestations, reducing reliance on chemical fertilisers and pesticides while improving food production efficiency. In this case, the idea of putting AI into agriculture was raised with the goal of optimising the production of food in relation to the growing global population and the projects are still moving in this direction. Additionally, they are trying to increase production, cultivate crops in a more responsible way, reduce air pollution and better treat the land which is often mishandled and corroded by an agriculture which is not very careful and far-sighted (Zha, 2020)[99].

What can be drawn from these considerations is that AI can be a very useful tool in most business sectors in which its integration could save time, resources, pollution, waste and optimise every process which it would be integrated into.

[98] Haleem, A., Javaid, M., Singh, R.P., Rab, S. and Suman, R. (2021). Hyperautomation for the enhancement of automation in industries. Sensors International

[99] Zha, J. (2020). Artificial Intelligence in Agriculture. Journal of Physics: Conference Series

Chapter 2 - AI in Smart Cities: Predictive Maintenance and Transport Optimisation

Once the main applications and evolutions of these technologies in the business sector have been defined, the aim of this dissertation is to understand how to apply these innovations to smart cities.

The business sector has served as an experimental ground for the development and refinement of Artificial Intelligence (AI), providing concrete examples of how data-driven systems, predictive analytics, automation, and optimisation tools can enhance performance and decision-making (Herath et al, 2022)[100]. As AI technologies matured within corporate environments, their successes have paved the way for broader applications across different domains, including the public sector and urban development (Tomor et al, 2021)[101].

Figure 22 - Key Pillars of a Smart City[102]

Cities are now capitalising on these advancements to improve their infrastructure management, mobility, sustainability, and citizen services, adapting the AI knowledge and technological frameworks that originally shaped business contexts. These know-hows are now being adopted to address the complex and dynamic challenges of urban environments, forming what are commonly known as 'smart cities'. For this reason, it was essential to first explore how AI has been implemented in business operations, in order to fully grasp its potential and strategic role in shaping the intelligent cities of tomorrow (Batty et al, 2012)[103]. Moving forward, this paper will look to explore these smart cities

[100] Herath, H.M.K.K.M.B. and Mittal, M. (2022). Adoption of artificial intelligence in smart cities: A comprehensive review. International Journal of Information Management Data Insights
[101] Tomor, Z., Przeybilovicz, E. and Leleux, C. (2021). Smart governance in institutional context: An in-depth analysis of Glasgow, Utrecht, and Curitiba
[102] Source: personal elaboration
[103] Batty, M., Axhausen, K.W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G. and Portugali, Y. (2012). Smart cities of the future. The European Physical Journal Special Topics

with a larger focus on predictive maintenance and transport optimisation, despite these technologies ultimately optimizing all aspects of a city's day-to-day operations.

2.1 Introduction: The Rise of Smart Cities

2.1.1 What is a Smart City?

A smart city is broadly defined as an urban area that leverages digital technology and data-driven solutions to improve the efficiency of its services, enhance its sustainability efforts, and raise the quality of life for its citizens. The European Commission (2022)[104] describes smart cities as places where traditional networks and services, such as transportation, energy, water, and waste management, are made more efficient through the integration of digital technologies for the benefit of residents and businesses. However, the concept extends well beyond digital upgrades, it encompasses a holistic vision of urban transformation, where technology is used strategically to foster innovation, improve urban governance, and ensure inclusive and participatory development (UN-Habitat, 2022)[105]. Smart cities are characterised by intelligent infrastructure, real-time data analytics, sustainable mobility, smart energy systems, and proactive governance models. For example, urban transport networks are enhanced through AI-powered traffic management systems that reduce congestion and emissions, while utility systems use sensor-based monitoring to optimise energy and water usage (OECD, 2024[106]; European Commission, 2024). At the same time, digital platforms support more responsive and transparent public administration, enabling citizens to interact with authorities, access services, and contribute to urban planning in more direct ways (UN-Habitat, 2022). Additionally, smart city initiatives often aim to address demographic challenges, such as the needs of an ageing population, by integrating assistive technologies and designing more accessible urban environments. The ultimate goal is to create cities that are not only more sustainable and resilient, but that are also more liveable and equitable, fostering economic growth and social cohesion through innovation and collaboration (European Commission, 2022; OECD, 2020; UN-Habitat, 2022).

---

[104] European Commission (2024). Smart cities. [online] commission.europa.eu.
[105] UN-Habitat, (2022), Annual report 2022UNITED NATIONS HUMAN SETTLEMENT PROGRAMME
[106] OECD. (2024). The OECD Programme on Smart Cities and Inclusive Growth

Dimension	Description
Intelligent Infrastructure	Integration of digital technologies in transport, energy, water, and waste systems
Sustainable Mobility	AI-powered traffic management and eco-friendly transportation to reduce emissions
Digital Governance	Use of digital platforms to enhance transparency, citizen engagement, and administrative efficiency
Citizen-Centric Services	Improved access to public services, inclusion of assistive technologies, participatory planning
Emerging Technologies	Adoption of IoT, big data, and AI to support real-time decision-making and system optimization
Strategic Goals	Foster sustainability, resilience, livealability, and social cohesion through innovation

Figure 23 - AI Technologies and Their Applications in Smart Cities[107]

2.1.2 The strategic role of Artificial Intelligence in enabling efficient, sustainable, and resilient urban environments

When dealing with the development of efficient, sustainable, and resilient urban environments, Artificial Intelligence (AI) and the supporting technologies described in the previous sections play a fundamental strategic role in becoming the transformative tool and guiding force for the redefinition of new urban governance models (OECD, 2024[108]; UN-Habitat, 2022[109]). It is precisely by applying such notions and advancements to the context of smart cities that AI, through the analysis of vast and complex datasets generated by urban infrastructures, environmental sensors, mobility networks, and citizen interactions, proceeds with the processing and interpretation of data in real time. This enables relevant stakeholders, such as the population, to optimise resource usage, minimise waste, and respond proactively both to routine demands and emergency scenarios (OECD, 2024).

[107] Source: personal elaboration
[108] OECD. (2024). The OECD Programme on Smart Cities and Inclusive Growth.
[109] UN-Habitat, (2022), Annual report 2022UNITED NATIONS HUMAN SETTLEMENT PROGRAMME.

For instance, AI-based traffic management systems can dynamically regulate traffic lights and reroute vehicles to reduce congestion and emissions. Another example of its implementation is in energy providers, whereby the use of predictive algorithms assists in balancing supply and demand, thereby decreasing environmental impact and enhancing grid stability (OECD, 2023).When it comes to the development of efficient, sustainable, and resilient urban environments, AI and its supporting technologies described in the previous sections play a fundamental strategic role in enabling this transformation.

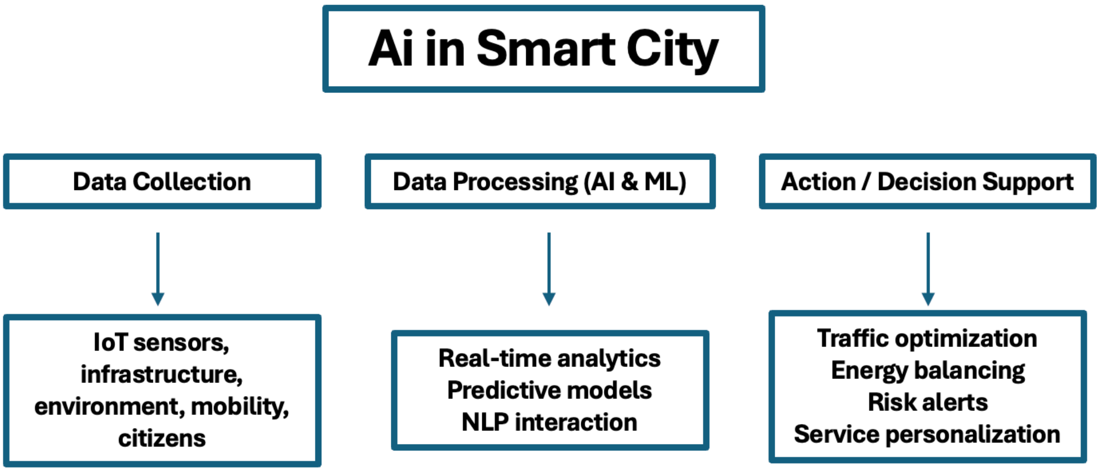

Figure 24 - How AI Supports Smart City Operations: From Data to Action[110]

Moreover, AI strengthens urban resilience by enhancing risk prediction and disaster preparedness via the use of Machine Learning (ML) models which can detect anomalies in environmental patterns, such as increased flood risk or air pollution surges and trigger early warning systems to protect public health and infrastructure (UN-Habitat, 2022). This risk avoidance technology application helps to prepare city workers to act promptly upon early warning signs whereby any damage may occur.

Additionally, AI can be fundamental as a tool to support long-term sustainability, enabling scenario analysis and evidence-based planning, thereby assisting policymakers in designing urban strategies aligned with environmental and social goals (European Commission, 2024).

[110] Source: personal elaboration

The integration of AI into city operations can also facilitate more inclusive governance: Natural Language Processing (NLP) tools and chatbots are increasingly employed to manage citizen feedback and service requests, contributing to a more responsive and transparent public administration.

Ultimately, the strategic value of AI lies in its ability to transform reactive urban management into a proactive, adaptive, and citizen-centred model, which is essential for building cities capable to thrive in the face of climate change, demographic shifts, and technological disruptions (UN-Habitat, 2022; European Commission, 2022), thereby counterbalancing the typical dysfunctions of public administrations.

AI Technology	Urban Application	Function
Predictive Algorithms	Energy, Environment	Demand forecasting, risk anticipation
ML / Anomaly Detection	Disaster Preparedness	Early warning systems
NLP / Chatbots	Governance / Citizen Services	Feedback management, request processing
Traffic Optimization AI	Mobility	Dynamic signal control, rerouting

Figure 25 - AI Tools and Functions in Predictive Urban Maintenance[111]

2.2 Predictive Maintenance in Urban Infrastructure

2.2.1 Digital Twins and Internet of Things in Smart cities: Foundations for Predictive Infrastructure Maintenance

In the context of predictive maintenance of urban infrastructures, the adoption and use of digital twins and Internet of Things (IoT) technology is taking on an increasingly strategic and central role.

These tools, defined as dynamic virtual models, are powered by data from physical assets, enabling city officials to monitor in real time the condition and performance of roads, bridges, energy networks, water systems, and even green spaces (Puomio, 2021)[112].

[111] Source: personal elaboration

[112] Puomio, S. (2021). What is an urban digital twin? - Forum Virium Helsinki. [online] Forum Virium Helsinki

When integrated with IoT sensors that are embedded in the urban environment, these models offer a constantly updated representation of infrastructure behaviour under varying conditions. This integration allows for the early detection of stress points, wear, or potential damage before they escalate into critical failures, by updating in real time and analysing every possible scenario accordingly (Puomio, 2021).

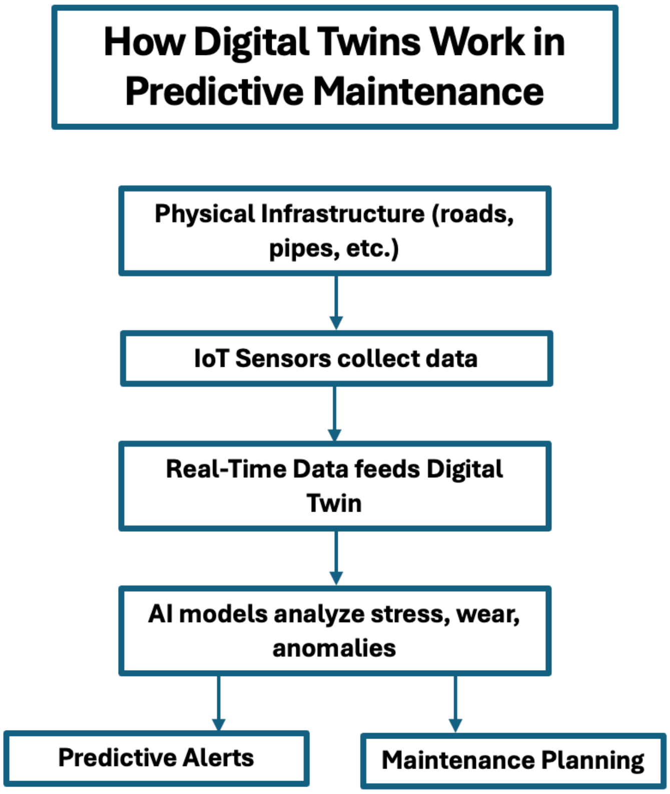

Figure 26 - How Digital Twins Work in Predictive Maintenance[113]

An important pioneer in this regard has been the city of Helsinki, which developed an extensive 3D city model known as "Helsinki 3D+," an initiative led by Forum Virium Helsinki and the Helsinki City Environment Division (Camus, 2022)[114]. In addition to urban planning, the model is also used for infrastructure monitoring and scenario simulation, such as assessing the impact of temperature changes on construction materials or vegetation. The digital twin incorporates real-time environmental data, thereby supporting

[113] Source: personal elaboration
[114] Camus, A. (2022). City of Helsinki Expands Digitalization with Citywide Digital Twin - Engineering.com

collaboration across different municipal departments and enhancing the efficiency and timeliness of maintenance-related decision-making in the capital (Forum Virium Helsinki, 2022).

In the United Kingdom, the Centre for Digital Built Britain (Walters, 2019)[115] has coordinated the National Digital Twin Programme, a government-backed initiative aimed towards promoting a national ecosystem of interconnected digital twins. The programme seeks to enhance the resilience and efficiency of the country's infrastructure through improved data sharing and lifecycle asset management.

From a general perspective, public agencies can anticipate degradation patterns and intervene proactively by integrating models across various sectors, including transport, energy, water, and construction, thereby extending asset lifespans and optimising public resource usage (Walters, 2019).

These cases of technological development and application demonstrate that digital twins, supported by real-time data from IoT networks, are not merely visualisation tools but powerful instruments for predictive infrastructure governance. They offer cities the opportunity to shift from reactive maintenance to proactive planning, aligning urban management with sustainability and resilience objectives (Camus, 2022; Forum Virium Helsinki, 2021). Most importantly, they contribute to improving citizens' everyday lives by enhancing cost-efficiency and the quality of public services.

2.2.2 AI-Powered Algorithms for Fault Detection and Maintenance Scheduling

Artificial Intelligence (AI) is growing in importance for predictive maintenance strategies within urban infrastructure, offering cities the ability to transition from reactive interventions to proactive asset management. AI-powered algorithms process real-time data collected from sensors embedded in critical components, such as bridges, underground pipelines, and electric grids, and detect patterns or anomalies that may signal early signs of wear, malfunction, or structural fatigue. These data-driven insights are then used to schedule maintenance operations in a timely and cost-effective manner, minimising the likelihood of disruptive failures.

[115] Walters, A. (2019). National Digital Twin Programme. [online] www.cdbb.cam.ac.uk.

In the electrical power sector, a 2025 systematic review published by Sohel Rana analysed AI-driven fault detection systems and reported classification accuracies ranging from 85% to 95% in detecting faults across various power system components. These systems also contributed to a 50% reduction in false alarms and significantly shortened recovery times after power interruptions by automating diagnostics and response workflows (Rana, 2025)[116].

In the field of urban water infrastructure, recent research from the University of Illinois employed Deep Reinforcement Learning (DRL) to optimise sewer pipe maintenance (Roa et al, 2024)[117]. The model dynamically adjusted the maintenance strategy based on pipe age and deterioration probability, shifting from a passive, low-cost approach for newer pipes to a proactive, failure-preventive approach for aging infrastructure. The simulation demonstrated a notable reduction in lifecycle costs while maintaining high service reliability (Roa et al, 2024).

Moreover, AI algorithms are increasingly used in Structural Health Monitoring (SHM) to assess the integrity of infrastructure such as bridges and public buildings. A 2024 infrastructure study highlights how AI models trained on sensor data, such as strain, vibration, and temperature, can detect early signs of structural degradation and optimise inspection schedules. The study emphasised that such systems enhance decision-making by enabling localised, risk-based prioritisation of maintenance, particularly in regions with limited budgets (Plevris et al, 2024)[118]

[116] Sohel Rana, (2025). AI-DRIVEN FAULT DETECTION AND PREDICTIVE MAINTENANCE IN ELECTRICAL POWER SYSTEMS: A SYSTEMATIC REVIEW OF DATA-DRIVEN APPROACHES, DIGITAL TWINS, AND SELF-HEALING GRIDS. American Journal of Advanced Technology and Engineering Solutions

[117] Lisandro Arturo Jimenez-Roa, Simão, T.D., Zaharah Bukhsh, Tiedo Tinga, Hajo Molegraaf, Jansen, N. and Stoelinga, M. (2024). Maintenance Strategies for Sewer Pipes with Multi-State Degradation and Deep Reinforcement Learning. PHM Society European Conference

[118] Vagelis Plevris and Papazafeiropoulos, G. (2024). AI in Structural Health Monitoring for Infrastructure Maintenance and Safety. Infrastructures

Domain	AI Technique Used	Detected / Optimized	Result
Power Systems	Classification Models (ML)	Fault types in electrical components	85–95% accuracy, 50% fewer false alarms
Sewer Maintenance	Deep Reinforcement Learning	Pipe deterioration and strategy optimization	Lifecycle cost reduction, improved reliability
Structural Health (SHM)	AI on strain/temp/vibration data	Degradation detection, inspection schedule optimization	Risk-based prioritization

Figure 27 - Impact of AI Across Infrastructure Domains[119]

These applications demonstrate the growing reliability and effectiveness of AI in supporting fault detection and maintenance planning, enabling agencies to extend the life of assets, reduce operating costs, and improve overall safety for residents.

2.2.3 Examples of Application in Everyday Life

The implementation of predictive maintenance powered by Artificial Intelligence (AI) is gaining traction across multiple sectors of urban infrastructure, including energy grids, water systems, and building management. These applications demonstrate how real-time monitoring and Machine Learning (ML) algorithms can be tailored to specific urban systems to improve operational reliability, reduce costs, and support sustainability objectives.

In the energy sector, Deutsche Bahn, Germany's national railway company, adopted AI-powered predictive maintenance to monitor and manage its extensive rail and electrical infrastructure. By analysing data from thousands of sensors installed along the railway network, the company developed ML models capable of predicting component failures before they occurred and according to a case study about this initiative, it led to a 25% reduction in maintenance costs and significantly decreased service disruptions caused by unexpected breakdowns (BestPractice.AI, 2022)[120].

---

[119] Source: personal elaboration

[120] Best Practice AI. (2016). AI Case Study | Deutsche Bahn reduces maintenance cost by 25% and delay-causing failures using machine learning

In the water sector, the city of Syracuse, New York, implemented a ML model to forecast water main breaks. The system analysed historical data, pipe material, installation dates, and environmental conditions to assess the failure risk of specific pipeline segments. In a comparative study published on the Cornell University (Kumar e al, 2018)[121], the AI model outperformed traditional heuristic-based approaches and allowed the city to prioritise maintenance based on risk levels, optimising both resources and response time (Kumar e al, 2018).

For building infrastructure, BrainBox AI has developed AI-based systems for autonomous HVAC optimisation in commercial buildings. One documented case involved a 15-story office building at 45 Broadway in New York City, where the AI system reduced energy consumption by 15.8%, resulting in annual savings of $42,000 and a reduction of 37 metric tons of CO_2 emissions. The AI platform uses real-time data from temperature, occupancy, and humidity sensors, and applies reinforcement learning to continuously improve HVAC efficiency without compromising occupant comfort (Chow, 2024)[122].

Sector	City / Company	AI Use Case	Outcome
Rail / Energy	Deutsche Bahn	Sensor-driven ML for predictive maintenance	-25% costs, fewer disruptions
Water Utilities	Syracuse, NY	ML model for water main break prediction	Better prioritization, faster response
Buildings	BrainBox AI (NYC)	AI for HVAC optimization via RL	-15.8% energy use, -37t CO_2, $42k saved

Figure 28 - AI Results Across Urban Infrastructure Domains[123]

These real-world implementations highlight the flexibility and effectiveness of predictive maintenance tools across different urban domains. By tailoring AI algorithms to

[121] Kumar, A., Asad, A., Brooks, B., Ali, V.R., Wilson, K.H., Kenney, C., Edelstein, S., Finch, A., Maxwell, A., Zuckerbraun, J. and Ghani, R. (2018). Using Machine Learning to Assess the Risk of and Prevent Water Main Breaks
[122] Chow, A.R. (2024). How AI Is Making Buildings More Energy-Efficient. TIME.
[123] Source: personal elaboration

infrastructure-specific requirements, cities can enhance service reliability, extend asset lifespans, and contribute to broader environmental goals.

2.2.4 Benefits: Cost Savings, Reduced Downtime, and Improved Public Safety

Integrating predictive maintenance systems based off of Artificial Intelligence (AI) into urban infrastructure, yields measurable benefits in terms of operational efficiency, financial savings, and public safety. One of the most immediate benefits, as noted above, is the reduction in maintenance costs, which can lead to significant long-term savings and increased operational efficiency. By predicting failures before they occur and targeting interventions exactly where they are needed, cities can reduce the frequency of emergency repairs and extend the lifespan of critical assets. A study by McKinsey & Company indicates that implementing AI-driven predictive maintenance can lead to a 20% reduction in maintenance costs and a 50% decrease in unplanned downtime, particularly benefiting sectors like energy and transportation (Dilda et al, 2017)[124].

Benefit Area	AI Contribution	Supporting Evidence
Cost Savings	Preventive maintenance → fewer emergency repairs	20–40% cost reduction (MDPI, 2023)
Downtime Reduction	Real-time anomaly detection, risk anticipation	Up to 50% reduction in unplanned downtime
Public Safety	Monitoring of structural stress, alerts before collapse	Avoided failures in bridges/tunnels (MDPI)
Infrastructure Lifespan	Timely, targeted maintenance scheduling	Extended asset life

Figure 29 - AI Applications and Sectoral Impact[125]

These considerations are even more impactful in contexts such as public transport, energy supply and water distribution, where reducing downtime is particularly critical, as service interruptions can have a widespread impact on economic productivity and daily life. A study conducted by the International Energy Agency (IEA) highlighted that predictive

[124] Dilda, V., Mori, L., Noterdaeme, O. and Schmitz, C. (2017). Manufacturing: Analytics unleashes productivity and profitability | McKinsey

[125] Source: personal elaboration

maintenance in smart grids improves grid stability, reduces blackouts, and supports the integration of renewable energy sources by making supply chains more responsive and adaptable (IEA, 2017)[126].

These results are not only valuable from a financial and logistical point of view, but also in a public safety context: AI algorithms can identify signs of structural stress or mechanical failures well before they become dangerous, allowing municipalities to prevent incidents related to the collapse of infrastructure or the malfunctioning of public utility systems. For example, predictive models used in structural health monitoring of bridges and tunnels can detect critical anomalies in real time, helping to avoid catastrophic failures, as noted in a 2024 review (Vagelis et al., 2024)[127].

Collectively, these benefits reinforce the strategic importance of predictive maintenance as an integral component of smart city development. By combining AI with sensor technologies and data analytics, cities are not only optimising infrastructure performance but also safeguarding their populations and making urban environments more resilient and cost-effective.

2.3 AI for Urban Mobility and Transport Optimisation

2.3.1 Real-Time Traffic Management Systems Powered by AI

Within cities, the management of daily traffic is increasingly influenced by Artificial Intelligence (AI), as urban areas continue to grow in both population and vehicular density. This growing reliance on AI is largely driven by its ability to make real-time, adaptive, and data-informed decisions, allowing for more efficient traffic flow, reduced congestion, and improved overall mobility across complex and ever-changing urban road networks. Traditional traffic signal systems are based on static data and pre-programmed schedules, which can lead to inefficiencies under fluctuating traffic conditions or changing user behaviours (Petrenko,2024)[128]. In contrast, AI-powered traffic management systems process continuous streams of data from cameras, road sensors,

---

[126] IEA (2017). Digitalization and Energy – Analysis.

[127] Vagelis Plevris and Papazafeiropoulos, G. (2024). AI in Structural Health Monitoring for Infrastructure Maintenance and Safety. Infrastructures

[128] Petrenko, V. (2024). AI in Transportation: How AI Technology is Revolutionizing Traffic Management

GPS devices, and connected vehicles to dynamically optimise traffic flow, reduce congestion, and respond to incidents with greater agility, adapting to evolving mobility patterns (Petrenko,2024)[129]. Not only does this improve travel times and reduce fuel consumption, but it also contributes to environmental sustainability by lowering greenhouse gas emissions and minimizing idle time. As urban mobility becomes more complex, AI stands out as a critical enabler of smarter, more responsive, and more sustainable transportation infrastructure.

City / System	Technology	Key Functions	Outcomes
Hangzhou – City Brain	AI traffic cameras, sensors	Signal optimization, emergency response	-15% travel time, +11% speed, <20s incident detect
Pittsburgh – Surtrac	Decentralized AI	Adaptive signal timing	-40% wait time, -25% travel, -20% emissions
Fremont – LYT	AI + cloud signal priority	Emergency vehicle routing	-69% response time
Solihull (UK)	AI signal + cyclist detection	Safety for vulnerable road users	Increased bike priority (trial phase)

Figure 30 - Cities' technologies and their outputs[130]

One of the most widely recognised and transformative implementations of AI in urban traffic control is the "City Brain" project in Hangzhou, China, developed in collaboration with Alibaba Cloud. This system collects real-time data from over 1,000 road intersections and traffic cameras, analysing it with AI to optimise signal timing, detect accidents, and coordinate emergency responses. Since its implementation, average travel times in key districts have decreased by up to 15%, and traffic speeds in the city centre have increased by 11% (World Economic Forum, 2018)[131]. The system can detect incidents in under 20 seconds and automatically reroute traffic to prevent bottlenecks, demonstrating the potential of AI to drastically enhance urban mobility.

[129] Petrenko, V. (2024). AI in Transportation: How AI Technology is Revolutionizing Traffic Management
[130] Source: personal elaboration
[131] World Economic Forum (January 2025). Blueprint to Action: China's Path to AI-Powered Industry Transformation

The implementation of AI systems like City Brain brings several notable benefits to urban environments. By enabling cities to respond to traffic conditions in real time, such systems contribute to smoother traffic flow, enhanced commuter experiences, and more efficient use of existing infrastructure. This, in turn, can support economic productivity by reducing delays and improving access to goods and services. However, challenges remain, particularly around data privacy, surveillance concerns, and the high cost of implementation. Cities must also address risks related to technological dependence and ensure robust governance to manage automated decision-making responsibly.

A similar innovation has been deployed in the United States through the Surtrac system, developed by researchers at Carnegie Mellon University and implemented in Pittsburgh. Using decentralised AI, the system manages more than 50 intersections by continuously monitoring real-time traffic patterns and adjusting signal timing based on actual vehicle flows rather than fixed schedules. As a result, vehicle wait times have been reduced by over 40%, travel times by 25%, and vehicle emissions by 20%, significantly improving both traffic efficiency and environmental outcomes (Smith et al, 2013)[132].

The Surtrac system in Pittsburgh differs from Hangzhou's City Brain by using decentralized AI, where each intersection makes real-time decisions based on local traffic. This allows for greater flexibility, scalability, and resilience, as the system can function even if parts fail. Unlike the centralized, data-heavy City Brain, Surtrac requires less infrastructure while still delivering major benefits, cutting wait times, travel times, and emissions, making it well-suited for cities with limited resources or diverse traffic needs. Nonetheless, its decentralised approach means intersections optimize traffic locally, which can lead to suboptimal outcomes at a broader network level. Unlike City Brain, which has a citywide view and can coordinate traffic holistically, including emergency responses, Surtrac lacks centralized oversight, making it less effective in managing large-scale events or citywide congestion patterns. Ultimately, both systems demonstrate the revolutionary impact of real-time AI-powered traffic management, showcasing how different models, centralized or decentralized, can significantly enhance

[132] Smith, S., Barlow, G., Xie, X.-F. and Rubinstein, Z. (2013). SURTRAC: Scalable Urban Traffic Control

urban mobility, safety, and sustainability when tailored to the specific needs and capacities of a city.

New AI-based traffic systems are also being developed to improve emergency vehicle prioritisation and multimodal traffic management. In Fremont, California, the city implemented the LYT system, which allows emergency vehicles to communicate with traffic signals via the cloud and request green lights when approaching intersections. This technology helped fire services reduce emergency response times across the city from 46 minutes to just 14 minutes, a 69% improvement (Holaday, 2024)[133], highlighting the life-saving potential of such systems when effectively integrated into traffic infrastructure.

AI is also supporting innovations in traffic management across Europe. In the United Kingdom, local governments have begun piloting AI-based traffic lights that prioritise vulnerable road users, such as cyclists and pedestrians. In Solihull, sensors detect approaching cyclists up to 30 meters away and automatically adjust signal phases to facilitate their crossing, enhancing safety and reducing conflicts with motor vehicles (Clatworthy, 2024)[134].

Together, these real-world applications underscore how AI is enabling a shift from reactive, manually operated traffic systems to responsive, automated infrastructures that adapt to real-time conditions. The result is not only a smoother and more efficient mobility experience, but also a significant contribution to sustainability, road safety, and urban liveability.

2.3.2 Dynamic Routing, Congestion Mitigation, and Optimisation of Public Transport Timetables

The recent advancements in Artificial Intelligence (AI) are not only delivering significant improvements in private vehicle traffic management but are also becoming a key driver in the transformation of public transportation systems. AI enables cities to respond in real time to changes in traffic conditions and passenger demand, supporting the dynamic

[133] Holaday, C. (2024). ‘Life-saving’ AI cuts travel time by 32 mins for vehicles racing to crash scenes – and it’s already ‘widely used’ [online] The US Sun

[134] Clatworthy, B. (2024). Hi-tech traffic lights could give cyclists the priority over cars. [online] Thetimes.com

adjustment of service schedules and vehicle availability. One of the most impactful applications in this domain is dynamic routing, where AI systems continuously evaluate traffic flow data to recommend or implement route modifications that reduce delays and enhance reliability (Reddy et al, 2021)[135].

Method	Type	Strengths	Limitations
Manual Scheduling	Heuristic	Human judgment, simple to implement	Inflexible, error-prone
Genetic / Memetic Algos	Metaheuristic	Handles complexity, semi-adaptive	Requires tuning, slower adaptation
DRL (DQN)	Deep Reinforcement Learning	Real-time, adaptive, data-driven	High computational cost, complex setup

Figure 31 - AI-Based Optimisation Tools for Public Transport Systems[136]

AI can integrate both historical and real-time data to flexibly adapt public transport schedules and routes, helping to avoid heavily congested areas and reduce service disruptions. Through predictive analytics, transport agencies can anticipate fluctuations in passenger demand by considering factors such as time of day, local events, and recurring travel patterns. These insights support strategic fleet allocation and the adjustment of service frequencies on specific lines, ultimately shortening waiting times, enhancing the passenger experience, and aligning service supply more closely with actual demand (Reddy et al, 2021).

Public transport authorities can use these predictive tools to dynamically adapt departure intervals in accordance with changing passenger volumes. An observation demonstrated that AI-powered scheduling can significantly reduce overcrowding during peak hours and improve vehicle distribution, particularly in metro and bus systems (Chowdhury et al. 2021).

A notable development in this field is the Deep Reinforcement Learning-based Timetable Optimisation model (DRL-TO), introduced to improve the real-time efficiency of bus operations. This method conceptualizes the scheduling task as a sequential decision-

[135] Reddy, P., Chaitanya, V. and Gupta, A., 2021. Optimising Public Transport Services using AI to Reduce Congestion in Metropolitan Areas

[136] Source: personal elaboration

making process, where a Deep Q-Network (DQN) is used to determine, on a minute-by-minute basis, whether a bus should be dispatched. The system can thus adjust departure intervals in real time, aligning them with passenger demand throughout the service window (Ai et al, 2021)[137]. Experimental evaluations show that DRL-TO outperforms traditional planning techniques such as memetic algorithms, genetic algorithms, and manual scheduling. On average, it reduces fleet usage by 8% and cuts passenger waiting times by 17%, demonstrating its effectiveness in adapting to fluctuating demand conditions (Ai et al, 2021).

The model incorporates several key state features to support decision-making, including load factor, vehicle utilisation rate, and the number of stranded passengers due to capacity constraints. A reward function is designed to balance the objectives of both operators and users, considering indicators such as full and empty load rates, waiting times, and unmet passenger demand. Furthermore, the model enhances demand-capacity matching accuracy at each bus stop by building upon existing methodologies for calculating carrying capacity (Ai et al, 2021).

Considering the growing urban populations and increasing mobility needs, AI-driven optimisation is no longer merely an innovation but a necessity. By improving operational efficiency, reducing environmental impact, and enhancing the passenger experience, AI is helping to build more sustainable and responsive urban transport networks, especially for this demographic that is in particular need.

2.3.3 Predictive fleet management and micro mobility

This domain also finds relevant application in the ride-sharing sector. Companies such as Uber and Lyft employ artificial intelligence algorithms to forecast demand patterns based on location, time, weather conditions, and local events, allowing for real-time adjustments in driver allocation and dynamic pricing (Government Fleet, 2024)[138].

Such capabilities ensure shorter waiting times for passengers and optimised fleet distribution, thereby enhancing both service efficiency and customer satisfaction.

---

[137] Ai, G., Zuo, X., chen, G. and Wu, B. (2021). Deep Reinforcement Learning based Dynamic Optimisation of Bus Timetable

[138] Government-fleet.com (2024). How Two Companies Are Using AI to Transform Fleet Management

Moreover, Artificial Intelligence (AI) systems monitor vehicle usage and driver behaviour, enabling more accurate predictions of operational needs and targeted recommendations for maintenance or route planning. These technologies also provide enhanced oversight, contributing to improved passenger and service safety (Government Fleet, 2024).

The field of micro mobility, which includes shared bicycles and electric scooters, has also been significantly impacted by AI, particularly in predictive vehicle repositioning and maintenance scheduling. By analysing geolocation data, usage trends, and environmental conditions, AI can identify areas of anticipated high demand and guide the strategic redistribution of fleet resources (Atom Mobility, 2024)[139]. This enhances the quality of service for end users while minimising downtime and maximising revenue generation for operators.

Some service providers have implemented AI-based systems capable of detecting physical damage or performance issues in real time, enabling quicker interventions that improve both safety and availability. As noted in recent industry analyses, such technologies are critical for managing fleet reliability in increasingly complex and distributed mobility environments (Atom Mobility, 2024).

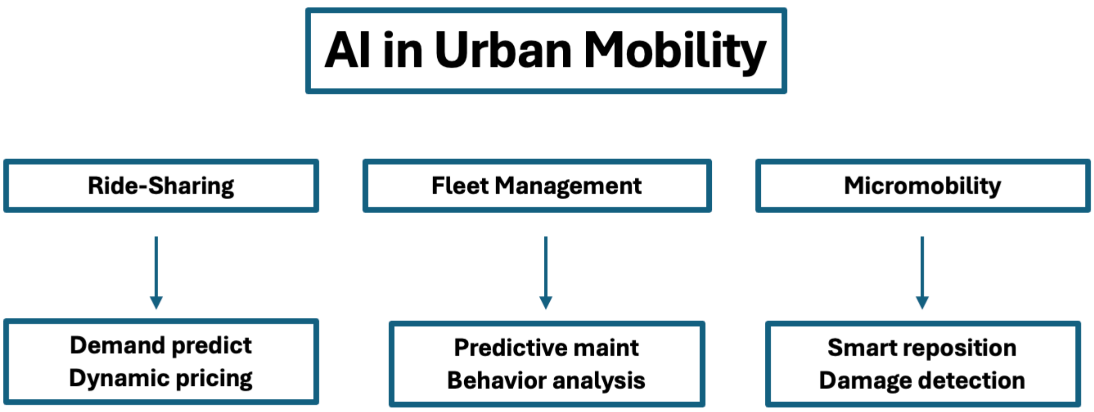

Figure 32 - AI in Urban Mobility[140]

As cities continue to expand and diversify their mobility offerings, AI-driven predictive fleet management is proving essential for coordinating multimodal services, reducing

[139] Atommobility.com. (2024). How is AI transforming the micromobility industry?
[140] Source: personal elaboration

operational inefficiencies, and ensuring that mobility systems remain responsive to shifting user needs and external conditions. Furthermore, the optimisation of these processes increasingly enables greater interconnectivity between various mobility options, making services more accessible and efficiently distributed across all necessary urban areas.

2.3.4 Integration with Mobility-as-a-Service platforms

Artificial Intelligence (AI) is becoming an increasingly integral part of the evolution of Mobility-as-a-Service (MaaS) platforms, defined as "a comprehensive mobility concept that integrates multiple public and private transport services through a single digital channel" (Dipartimento per la trasformazione digitale, N/A)[141]. These platforms aim to provide seamless, multimodal transport solutions by integrating various mobility services into a unified, user-centred interface.

AI enhances these platforms by analysing large datasets to optimise route planning, personalise user experiences, and improve operational efficiency (Infosys Limited, 2025)[142]. For example, Los Angeles' GoLA app uses AI-based route optimisation, integrating real-time traffic data to forecast commuter demand and adjust services accordingly, thereby offering flexible transport options such as ridesharing, cycling, and public transit (Matter, 2024)[143].

AI also facilitates the coordination and planning of emerging transportation modes, including autonomous vehicles and drones, within MaaS ecosystems. By leveraging Machine Learning (ML) algorithms, these platforms can dynamically adapt to changing traffic conditions and user preferences, ensuring timely and efficient service delivery (Matter, 2024).

[141] Dipartimento per la trasformazione digitale. (n.d.). Mobility as a Service for Italy
[142] Infosys Limited (2025). AI powered MaaS. [online] Infosys.com
[143] Mattar, A. (2024). Harnessing IoT, Big Data, and AI to Drive Mobility as a Service (MaaS) in Smart Cities

AI Capability	MaaS Function	User / City Benefit
Route optimization	Multimodal trip planning	Shorter travel, seamless user experience
Demand forecasting	Service availability adjustment	Reduced wait time, fewer missed connections
User behavior modeling	Personalized mobility suggestions	Satisfaction, accessibility
Coordination with AV/Drones	Mode integration	Flexibility, innovation

Figure 33 - AI Capabilities for User Benefit[144]

In addition, AI contributes to the development of knowledge-based frameworks that integrate various types of mobility data, enabling MaaS platforms to deliver personalised services tailored to individual traveller needs (Rajabi et al., 2023)[145]. As a result, the integration of AI into MaaS platforms not only enhances user satisfaction through efficient and customized mobility solutions but also promotes sustainability by optimising resource use and reducing congestion.

2.4 Environmental and Safety Monitoring through AI

2.4.1 Air quality and noise pollution monitoring using AI and sensor networks

Within the context of smart city integration, Artificial Intelligence (AI) is increasingly proving essential for environmental monitoring, particularly in assessing air quality and noise pollution in urban areas. By integrating AI with sensor networks, cities can collect and analyse extensive environmental data, thereby enhancing public health and urban planning.

In the field of air quality monitoring, AI enables the development of predictive models that forecast pollutant levels based on historical data and meteorological conditions. For instance, Machine Learning (ML) techniques such as Random Forest have achieved

[144] Source: personal elaboration

[145] Rajabi, E., Nowaczyk, S., Sepideh Pashami, Bergquist, M., Geethu Susan Ebby and Summrina Wajid (2023). A Knowledge-Based AI Framework for Mobility as a Service. Sustainability

accuracy rates of up to 98.2% in air pollution forecasting, facilitating timely interventions to mitigate negative health impacts (Chadalavada et al., 2025)[146].

Regarding noise pollution, AI enhances the analysis and monitoring of urban soundscapes. Techniques like Urban Sound Tagging (UST) use AI to map the distribution of acoustic pollution, supporting environmental protection efforts. By identifying the primary sources of noise, such as road traffic, industrial activities, or construction sites, and through ML algorithms, these systems are capable of recognizing recurring patterns and providing precise mapping of the areas most affected by the phenomenon (Quang Thao et al., 2023)[147].

Aspect	Air Quality Monitoring	Noise Pollution Monitoring
AI Techniques	Machine Learning (Random Forest, Regression)	Urban Sound Tagging, Pattern Recognition
Data Sources	Meteorological sensors, pollutant levels	Audio sensors, ambient sound recordings
Outputs	Pollution forecasts, exposure maps	Noise maps, source identification
Applications	Public health alerts, traffic regulation	Smart barriers, urban planning
Accuracy / Results	Up to 98.2% accuracy in prediction (2024 study)	High-resolution spatial analysis of urban noise

Figure 34 - AI for Air Quality and Noise Pollution Monitoring[148]

Another relevant aspect is the potential to implement dynamic mitigation strategies. Through predictive analytics, AI can suggest targeted and adaptive corrective measures,

[146] Chadalavada, S., Faust, O., Salvi, M., Seoni, S., Raj, N., Raghavendra, U., Gudigar, A., Barua, P.D., Molinari, F. and Acharya, R. (2024). Application of artificial intelligence in air pollution monitoring and forecasting: A systematic review. Environmental Modelling & Software

[147] Quang Thao, L., Duc Cuong, D., Thi Tuong Anh, T. and Duc Luong, T. (2023). Profiling of Urban Noise Using Artificial Intelligence. Computer Systems Science and Engineering

[148] Source: personal elaboration

such as regulating traffic flows or installing smart noise barriers, thus contributing to a more efficient and proactive management of urban noise pollution (Garcia, 2022)[149].

2.4.2 AI-powered surveillance for public safety and ethical implications

Artificial Intelligence (AI) is reshaping the way that cities approach public safety, offering advanced tools for real-time surveillance, anomaly detection, and risk prevention. Through the use of Machine Learning (ML) algorithms and computer vision, AI systems can process footage from urban camera networks to identify suspicious behaviours, unattended objects, or unusual patterns in crowd movements.

These systems are increasingly being adopted in smart cities to support law enforcement and emergency services by enabling faster and more informed decision-making. For instance, the Domain Awareness System (DAS) implemented by the New York Police Department integrates data from closed-circuit cameras, environmental sensors, and other sources to enable real-time monitoring and risk assessment based on behavioural and physical attributes (Zubair)[150]. Similarly, private-sector applications such as the AI-powered system developed by the French start-up Veesion have been deployed in thousands of retail locations worldwide to detect theft and abnormal activity, demonstrating AI's capability to identify threats in real time within complex environments (Hubar, 2025)[151].

However, the growing use of AI in surveillance raises critical ethical and legal concerns, as these technologies often rely on the mass collection of personal data, potentially permitting invasive surveillance practices if not properly regulated. This has contributed to a growing consensus among scholars and policymakers that urban AI systems must be designed with transparency, accountability, and privacy safeguards at their core (Cavoukian, 2010)[152].

[149] Garcia, E. (2022). AI-Driven Noise Pollution Monitoring and Mitigation in Smart Cities.
[150] Zubair, A. (n.d.). Domain Awareness System.
[151] Hubar, N. (2025). AI business technology takes on shoplifters and admin drag. [online] @FinancialTimes
[152] Cavoukian, A. (2010). Privacy by design: the definitive workshop. A foreword by Ann Cavoukian, Ph.D. Identity in the Information Society

These concerns also extend to issues such as algorithmic bias, which further complicates the ethical landscape. Studies have shown that AI models trained on biased datasets can produce discriminatory outcomes, especially in high-stakes areas such as policing and access to public services (Cavoukian, 2010). To mitigate these risks, regulatory frameworks have been proposed that emphasise principles of fairness and “privacy by design,” a concept advanced by Ann Cavoukian, to ensure that ethical considerations are embedded into the design and deployment of AI technologies from the outset (Cavoukian, 2010).

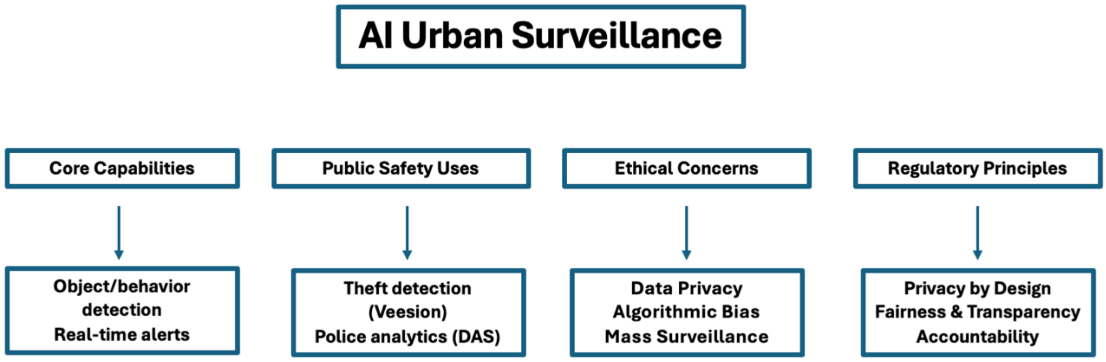

Figure 35 - AI Urban Surveillance

2.5 Challenges and Barriers to AI Adoption in Smart Cities

2.5.1 Financial, technical, and organisational constraints

The previous section illustrates that the adoption of Artificial Intelligence (AI) in smart cities has a well-established and growing potential to enhance the efficiency and responsiveness of urban systems. However, this transformation is not without significant financial, technical, and organisational constraints and limitations.

From a financial standpoint, implementing AI systems requires substantial capital investment in infrastructure such as sensor networks, high-performance computing, secure data centres, and ongoing algorithm training. These costs are often beyond the reach of many municipalities, particularly in developing contexts where budget constraints force local governments to prioritise basic services over technological innovation. Even in wealthier urban environments, long-term cost-benefit assessments, and uncertainties regarding return on investment can delay or inhibit AI adoption (Wolniak et al, 2024)[153].

On the technical side, challenges stem from the lack of standardized frameworks and protocols for integrating AI technologies into heterogeneous systems. Many components of smart cities, such as traffic control, waste management, and energy networks, are managed by various stakeholders and vendors, often using proprietary platforms (Wolniak et al, 2024). This results in fragmented data silos, limited interoperability, and barriers to cross-domain data sharing, all of which hinder the full implementation of AI-driven services and conflict with the underlying goals of complementarity, connectivity, and responsiveness that smart systems aspire to. Furthermore, the quality and availability of urban data remain inconsistent. Many cities lack the infrastructure to collect and process high-quality, real-time data at scale, which is essential for training effective AI models.

Organisational barriers are equally significant. Public administrations frequently face a shortage of in-house expertise capable of managing and interpreting complex AI systems. This issue is compounded by bureaucratic inertia, resistance to innovation, and siloed decision-making structures, which slow the integration of AI tools into daily operations (Tangi et al, 2023)[154]. Moreover, the successful implementation of AI in urban governance largely depends on institutional capacity, leadership commitment, and a cultural shift towards data-driven decision-making. Without mechanisms for cross-sector coordination and supportive governance frameworks, AI initiatives risk remaining isolated projects with limited long-term impact, and their transformative potential may only be partially realized.

[153] Wolniak, R. and Stecuła, K. (2024). Artificial Intelligence in Smart Cities: Applications, Barriers, and Future Directions: A Review. Smart Cities

[154] Tangi, L., Colin van Noordt and Rodriguez, P. (2023). The challenges of AI implementation in the public sector. An in-depth case studies analysis

Barrier Type	Description	Examples / Consequences	Suggested Actions
Financial	High upfront costs for sensors, HPC, data centers	Delayed adoption, especially in developing cities	PPPs, long-term planning
Technical	Fragmented systems, lack of interoperability, data gaps	Inconsistent data quality, poor model training	Standardization, data infrastructure investment
Organizational	Lack of expertise, resistance to change, siloed structures	Slow integration, limited impact	Upskilling, culture shift, institutional reform

Figure 36 - Mitigation for Barriers to AI Adoption[155]

To ensure that these barriers are not insurmountable and that AI integration in smart city ecosystems succeeds, more than just technological readiness is required. Local and central governments must engage in strategic planning, foster robust public-private partnerships, upskill the workforce, and pursue appropriate institutional reforms. These actions are essential not only to unlock AI's transformative potential but also to safeguard the critical interests of the broader public (Wolniak et al, 2024).

2.5.2 Risks related to surveillance, data security, and social inequality

In addition to the financial and technical limitations previously discussed, the adoption of Artificial Intelligence (AI) in smart cities also raises critical concerns regarding surveillance practices, data security, and the potential exacerbation of social inequalities. The increasing use of AI-enhanced surveillance systems, such as facial recognition and predictive analytics, poses serious questions about civil liberties and the balance between public safety and personal privacy (Feldstein, 2021)[156]. While these technologies can contribute to enhanced security, they also risk enabling mass surveillance and eroding democratic freedoms, particularly if deployed without sufficient transparency or regulatory oversight.

[155] Source: personal elaboration
[156] Feldstein, S. (2021). The rise of digital repression: How technology is reshaping power, politics, and resistance. Oxford University Press

Data security presents a major challenge, especially in light of the unprecedented volume and sensitivity of the personal information being collected. Smart city infrastructures typically rely on the aggregation and centralisation of large amounts of personal and environmental data, making them attractive targets for cyberattacks (Mittelstadt et al., 2016)[157]. The misuse or leakage of such sensitive data can lead to identity theft, discriminatory profiling, or the loss of public trust, undermining the very principles on which these systems are intended to operate. The complexity of securing AI systems, especially when integrated with legacy urban infrastructure, further compounds this issue.

Beyond these direct risks to privacy and security, AI adoption may reinforce or deepen existing patterns of social inequality. Disparities in digital literacy, access to infrastructure, and algorithmic representation can systematically disadvantage marginalised communities (Mittelstadt et al., 2016). A practical example lies in the way that AI systems used in urban services may be trained on biased data, resulting in unequal access to housing, mobility, or social services. Moreover, AI-driven automation could contribute to labour displacement in low-income sectors, disproportionately affecting vulnerable populations (Mittelstadt et al., 2016).

[157] Mittelstadt, B.D., Allo, P., Taddeo, M., Wachter, S. and Floridi, L. (2016). The Ethics of algorithms: Mapping the Debate. Big Data & Society

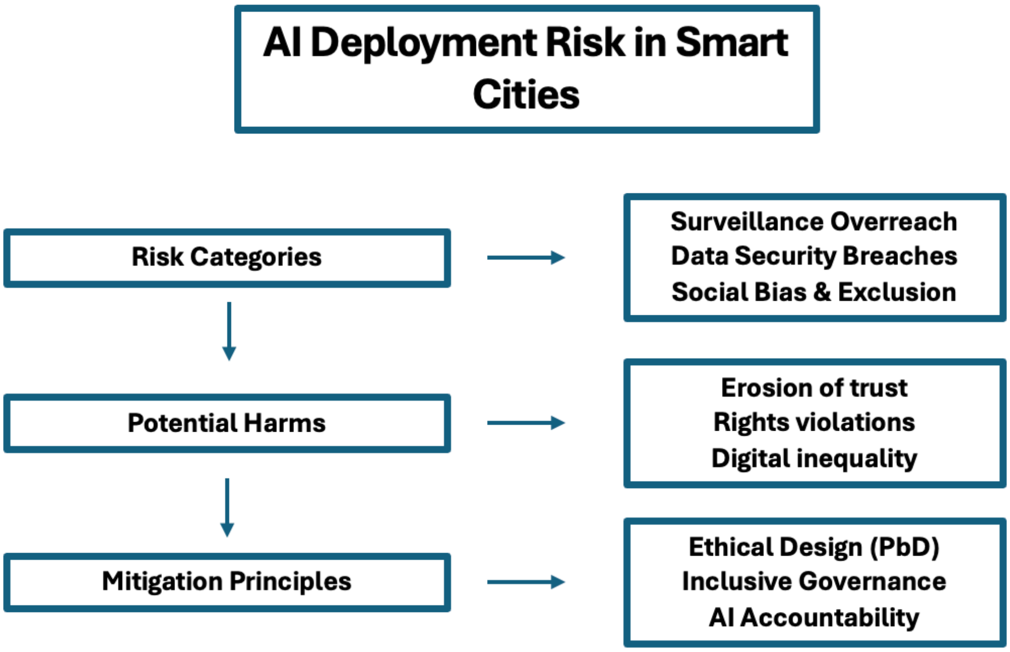

Figure 37 - AI Deployment Risk in Smart Cities[158]

To address these challenges, policymakers and urban planners must establish robust governance frameworks that promote transparency, accountability, and equity. This includes the implementation of strong data protection standards, the design of AI systems guided by ethical principles such as the previously cited "privacy by design," and the assurance that smart city initiatives are inclusive and responsive to the needs of all citizens, not only those who are digitally connected or economically advantaged (Mittelstadt, 2016)[159].

2.5.3 The importance of inclusive, citizen-centric AI design

It is important to adopt an inclusive, citizen-centred approach to ensure that the adoption of Artificial Intelligence (AI) in smart cities is equitable and responsive to the needs of all citizens. This entails actively involving residents in the decision-making process and addressing their concerns, ensuring that AI-based solutions are designed with and for the

[158] Source: personal elaboration

[159] Cavoukian, A. (2010). Privacy by design: the definitive workshop. A foreword by Ann Cavoukian, Ph.D. Identity in the Information Society

community, and grounded in the principles of transparency, fairness, and accountability, key elements for achieving broad public acceptance (Simonofski et al, 2021)[160].
A central component of this approach is the creation of participatory platforms that facilitate the interaction between citizens and local authorities, helping to clarify the boundaries, expectations, and necessities surrounding the implementation of such technologies. These platforms should be accessible and user-friendly, enabling citizens to contribute meaningfully to the co-creation of urban services. Moreover, the design of AI tools must reflect a deep understanding of community needs and expectations, in close collaboration with local governments, to ensure that technological solutions are aligned with broader societal goals (Simonofski et al, 2021).
Additionally, the implementation of AI in smart cities must directly address the ethical implications and privacy concerns previously discussed. It is crucial to develop regulatory frameworks that safeguard personal data and promote the responsible use of AI. This includes adopting measures to prevent algorithmic discrimination and ensuring that automated decision-making does not perpetuate or exacerbate existing social inequalities (Sanchez et al., 2024)[161].
Ultimately, achieving truly inclusive urban design requires integrating AI with participatory planning practices that actively engage local communities. This approach allows for the combination of data-driven analysis with residents' contextual knowledge, resulting in more effective and widely accepted solutions. For example, AI-based tools can be used to visualise alternative urban scenarios, helping citizens better understand and influence planning decisions (UNDP, 2024)[162].

[160] Simonofski, A., Hertoghe, E., Steegmans, M., Snoeck, M. and Wautelet, Y. (2021). Engaging citizens in the smart city through participation platforms: A framework for public servants and developers. Computers in Human Behavior
[161] Sanchez, T.W., Brenman, M. and Ye, X. (2024). The Ethical Concerns of Artificial Intelligence in Urban Planning. Journal of the American Planning Association
[162] UNDP. (2024). Bringing Communities Together Through AI-Driven Urban Planning

Principle	Implementation in Smart Cities
Transparency	Open AI systems with visible logic and decision tracking
Fairness & Inclusion	AI trained on representative data, avoiding discrimination
Participation	Citizen engagement platforms for planning, feedback, co-design
Accountability	Clear responsibility over automated decisions
Privacy by Design	Integration of data protection from system inception

Figure 38 - Challenges of Ethical AI Governance in Urban Environments[163]

[163] Source: personal elaboration

Chapter 3 - Case Studies: AI Implementation in Leading Smart Cities

3.1 Background and Urban Context

Artificial Intelligence (AI) has thus established itself as a fundamental and indispensable tool for addressing the increasingly complex challenges faced by urban environments worldwide. It has also become a cornerstone in enhancing the quality of life for citizens across all cities.

As outlined in the previous chapters, cities are increasingly committed to improving sustainability, optimizing their resource use, and enhancing the well-being of their residents. Among these cities, some stand out for their achievements in reaching these goals and for further advancing progress made in previous years. In particular, the cities of Zurich, Oslo, Geneva, Dubai, and Abu Dhabi, ranked highest in the 2024 Global Ranking (International Institute for Management Development, 2025)[164], are of notable interest. These cities should be regarded as benchmarks, as they exemplify cutting-edge AI implementation and have been selected for their remarkable achievements and successful strategic approaches to integrating intelligent technologies into urban governance.

The objective of this chapter is therefore to explore how the considerations discussed thus far can be effectively and successfully applied in cities around the world, transforming theoretical aspirations into concrete, proactive cases of technological implementation.

[164] IMD. (2025). IMD_Smart_City_2025_Report.pdf

3.1.1 Why these cities?

City	City Rank 2025	Rating 2025	Structure 2025	Technology 2025	City Rank 2024	Change
Zurich	1	AAA	AAA	AAA	1	0
Oslo	2	AAA	AAA	AAA	2	0
Geneva	3	AAA	AAA	AAA	4	+1
Dubai	4	A	A	A	12	+8
Abu Dhabi	5	A	A	A	10	+5
London	6	AA	AAA	AAA	8	+2
Copenhagen	7	AAA	AAA	AA	6	-1
Canberra	8	AAA	AAA	A	3	-5
Singapore	9	AAA	AAA	AAA	5	-4
Lausanne	10	AAA	AA	AA	7	-3

Figure 39 - IMD Smart City Index 2025: Results In 2025 city ranking order and 2024 comparison[165]

Zurich, renowned for its high quality of life and its attention to the environment, has strategically positioned itself at the forefront of sustainable urban management. The city has set ambitious goals such as the achievement of the 2000-watt society target, namely by lowering the average consumption of each citizen to this amount, significantly reducing per capita energy consumption and greenhouse gas emissions (Oyadeyi et al, 2025)[166].
As for Zurich's strategic objective, the city is committed to leveraging Artificial Intelligence (AI) and the Internet of Things (IoT) primarily in urban mobility and infrastructure management, enabling real-time monitoring and dynamic resource allocation to improve energy efficiency and reduce traffic congestion (Stadt-zuerich.ch., 2024)[167].
Oslo, the capital of Norway, has established itself as a global leader in urban innovation, specifically aiming for zero-emission public transportation systems by 2025 (Fabbrocino, R., 2023)[168]. In order to achieve this goal, a key component of Oslo's smart transformation strategy is the widespread adoption of electric vehicles supported by AI-enhanced charging infrastructure and predictive traffic management systems. Through sophisticated Machine Learning (ML) algorithms, Oslo analyses traffic patterns and

[165] Source: personal reworking from IMD. (2025). IMD_Smart_City_2025_Report.pdf
[166] Oyadeyi, O.A. and Oyadeyi, O.O. (2025). Towards Inclusive and Sustainable Strategies in Smart cities: a Comparative Analysis of Zurich, Oslo, and Copenhagen
[167] Stadt-zuerich.ch. (2024). Smart City
[168] Fabbrocino, R. (2023). Oslo becoming the world's first capital with a zero-emissions public transport system. [online] Lampoon Magazine

dynamically adjusts public transport schedules, significantly reducing congestion and emissions (EU Urban Mobility Observatory, 2024)[169].

Geneva's rise to third place in the 2025 Index is attributed to its inclusive governance model and citizen-centred digital services. The city has adopted AI to enhance accessibility and equity in public services, with particular emphasis on participatory urban planning, real-time data analysis for mobility management, and the optimization of smart utilities. Geneva's initiatives prioritize the ethical implementation of AI, data privacy, and transparent algorithmic governance (Mayors of Europe, 2024)[170].

Dubai represents a dynamic shift towards high-tech urbanism in the Middle East. After climbing eight positions in the IMD ranking, Dubai is redefining smart city development through large-scale investments in AI-based services, including autonomous mobility, digital twin platforms, and blockchain-based governance. Dubai's "Smart Dubai 2021" roadmap laid the foundation for a comprehensive digital ecosystem, positioning the city as a global testbed for AI innovation (AL-Dabbagh, R., 2022)[171].

Abu Dhabi complements Dubai's momentum with a smart city strategy centred on sustainability. Ranked fifth globally, Abu Dhabi has integrated AI into public transport planning, smart energy grids, and environmental monitoring systems. The city's focus on green urbanism is reinforced by the application of predictive analytics and AI in waste management, water resource conservation, and smart irrigation projects. In particular, these initiatives align with the broader framework of the UAE's Vision 2030, which promotes sustainable economic and infrastructural development (Abu Dhabi Media Office, 2025)[172].

[169] EU Urban Mobility Observatory. (2024). Data-driven technology powers Oslo's sustainable electric bus fleet

[170] Mayors of Europe. (2024). Transforming Urban Living - Insights from the IMD Smart City Index 2024 on Europe's Leading and Lagging Cities | Mayors of Europe

[171] AL-Dabbagh, R. (2022). Dubai, the sustainable, smart city. Renewable Energy and Environmental Sustainability

[172] Abu Dhabi Media Office (2025). Abu Dhabi ranks 5th globally in 2025 IMD Smart City Index. [online] Mediaoffice.abudhabi

3.1.2 Strategic Goals of Smart Transformation

The smart transformation strategies pursued by Zurich, Oslo, Geneva, Dubai, and Abu Dhabi are characterized by highly specific, results-oriented objectives that position Artificial Intelligence (AI) not merely as an operational tool, but as an enabler of systemic urban change.

In Zurich, the strategic objective is to achieve long-term environmental neutrality and energy autonomy, aiming to align all urban sectors, such as transport, infrastructure, and public services, with the city's 2000-watt society goal. To this end, AI systems are employed to optimize urban energy networks in real time and to integrate predictive analytics into municipal decision-making processes, particularly in the energy and mobility sectors (Oyadeyi et al, 2025)[173].

Oslo's smart city strategy, on the other hand, focuses on maintaining global leadership in zero-emission mobility and achieving carbon neutrality by 2030. AI plays a crucial role in developing adaptive public transport schedules, enabling predictive maintenance of electric fleets, and supporting real-time environmental monitoring to ensure the achievement of emission reduction targets (EU Urban Mobility Observatory, 2024)[174].

Geneva has defined its strategic objectives around building a digitally inclusive city that upholds ethical standards in technology implementation. The city prioritizes AI governance frameworks designed to prevent algorithmic bias and ensure equitable access to digital services across socioeconomic groups, particularly in the sectors of public health and education (Mayors of Europe, 2024)[175].

Dubai's transformation program centres on the Dubai 10X initiative, which aims to deliver public services operating ten years ahead of other global cities. The city integrates AI to create predictive government services, optimize urban logistics, and foster an AI-driven

---

[173] Oyadeyi, O.A. and Oyadeyi, O.O. (2025). Towards Inclusive and Sustainable Strategies in Smart cities: a Comparative Analysis of Zurich, Oslo, and Copenhagen

[174] EU Urban Mobility Observatory. (2024). Data-driven technology powers Oslo's sustainable electric bus fleet

[175] Mayors of Europe. (2024). Transforming Urban Living - Insights from the IMD Smart City Index 2024 on Europe's Leading and Lagging Cities | Mayors of Europe

entrepreneurial ecosystem aimed at maximizing competitiveness and quality of life (AL-Dabbagh, R., 2022)[176].

Abu Dhabi's strategy emphasizes building environmental resilience and advancing the digital economy. Strategic initiatives include the use of AI to anticipate infrastructure stress, optimize water and energy consumption, and develop intelligent governance platforms capable of dynamically adapting to changing urban conditions (Abu Dhabi Media Office, 2025)[177].

In these five cities, Artificial Intelligence is strategically integrated into broader frameworks of sustainable urban development, inclusivity, and economic competitiveness, demonstrating a paradigmatic shift from fragmented technological implementations to comprehensive, goal-oriented models of urban governance.

3.1.3 Key Stakeholders Involved

The successful implementation of AI-based smart city strategies in Zurich, Oslo, Geneva, Dubai, and Abu Dhabi largely relies on the active participation and coordination of multiple stakeholder groups, each playing a distinct yet interdependent role.

In Zurich, the municipal administration, particularly the City of Zurich's Smart City Hub, operates as the central governance actor, setting strategic priorities and ensuring alignment with broader social goals, such as the previously mentioned 2000-watt society objective. Collaboration with local universities, such as ETH Zurich, and public utilities like EWZ, one of Switzerland's largest energy providers, ensures that technological developments in AI and Internet of Things (IoT) are both scientifically grounded and practically achievable (EWZ, 2024)[178].

In Oslo, the municipality works closely with national bodies such as the Norwegian Public Roads Administration and private technology innovators to advance its zero-emission transport program. Public-private partnerships have been essential for expanding the

[176] AL-Dabbagh, R. (2022). Dubai, the sustainable, smart city. Renewable Energy and Environmental Sustainability

[177] Abu Dhabi Media Office (2025). Abu Dhabi ranks 5th globally in 2025 IMD Smart City Index. [online] Mediaoffice.abudhabi

[178] ewz. (2024). 2,000-watt society | Our commitment | ewz

electric vehicle infrastructure and implementing AI-based traffic management systems (EU Urban Mobility Observatory, 2024)[179].

Geneva's approach to smart urban governance emphasizes inclusivity, relying not only on public authorities such as the City of Geneva but also on NGOs, academic research centres (such as the University of Geneva), and citizen-led initiatives. This collaborative model is particularly evident in projects aimed at bridging the digital divide and promoting the ethical implementation of AI (Mayors of Europe, 2024)[180].

Dubai's transformation into a Smart City is strongly driven by government-led innovation bodies, particularly Smart Dubai and the Dubai Future Foundation. These organizations orchestrate the deployment of AI across various sectors, collaborating with international tech companies and local entrepreneurs within public innovation frameworks such as the Dubai 10X initiative (AL-Dabbagh, R., 2022)[181].

In Abu Dhabi, a combination of government agencies (e.g., the Department of Municipalities and Transport), technology solution providers, and academic institutions such as Khalifa University similarly collaborate to advance digital resilience and sustainability. The Abu Dhabi Digital Authority plays a pivotal role in ensuring the seamless integration of smart services into urban life (Abu Dhabi Media Office, 2025)[182].

Across all five cities, the integration of AI into urban systems is not merely a technological project but a socio-technical enterprise that requires the active engagement of governments, private sector actors, academia, and civil society. This multi-stakeholder governance model is essential to ensuring that AI innovations are aligned with broader social values, technological robustness, and long-term urban sustainability.

[179] EU Urban Mobility Observatory. (2024). Data-driven technology powers Oslo's sustainable electric bus fleet

[180] Mayors of Europe. (2024). Transforming Urban Living - Insights from the IMD Smart City Index 2024 on Europe's Leading and Lagging Cities | Mayors of Europe

[181] AL-Dabbagh, R. (2022). Dubai, the sustainable, smart city. Renewable Energy and Environmental Sustainability

[182] Abu Dhabi Media Office (2025). Abu Dhabi ranks 5th globally in 2025 IMD Smart City Index. [online] Mediaoffice.abudhabi

3.2 Zurich: Pioneering Energy Efficiency and Urban Mobility

As previously outlined, Zurich is a global pioneer in the operationalization of Artificial Intelligence (AI) within the realm of sustainable urban management, a strategy that has secured its first-place ranking for five consecutive years. Rather than viewing AI as a supplementary technological tool, Zurich has strategically embedded it at the core of its urban development policies, particularly in the areas of energy efficiency and mobility optimization.

This application has been pursued with a focus on long-term objectives, especially those related to environmental sustainability and energy consumption.

Building on its longstanding commitments, most notably the environmental objective of achieving a 2000-watt society, the city has developed a comprehensive smart city strategy that integrates real-time data analytics, Machine Learning (ML) algorithms, and Internet of Things (IoT) networks across various sectors (Oyadeyi et al, 2025[183]; Stadt-zuerich.ch., 2024[184]).

Among these initiatives, a fundamental principle of Zurich's approach is the harmonization of technological innovation with environmental responsibility. The city has focused on implementing AI to enhance the energy efficiency of public services, dynamically manage street lighting systems, and predictively regulate traffic flows. These initiatives are not developed in isolation but are coordinated through a systemic governance model led by the Smart City Zurich Hub, with the active collaboration of public utilities, research institutions, and private technology partners (EWZ, 2024)[185].

The following sections provide an in-depth analysis of Zurich's strategic vision and its concrete initiatives for pioneering AI-based, energy-efficient urban mobility solutions. Particular attention will be devoted to the operation of IoT infrastructures, the implementation of adaptive algorithms for traffic and lighting management, and the measurable impacts achieved in terms of energy savings, emission reductions, and traffic optimization.

[183] Oyadeyi, O.A. and Oyadeyi, O.O. (2025). Towards Inclusive and Sustainable Strategies in Smart cities: a Comparative Analysis of Zurich, Oslo, and Copenhagen. *Research in Globalization*
[184] Stadt-zuerich.ch. (2024). Smart City
[185] ewz. (2024). 2,000-watt society | Our commitment | ewz

3.2.1 Overview of Zurich's Smart City Strategy and Goals

Zurich's Smart City strategy represents an integrated and systemic approach to sustainable urban development, positioning Artificial Intelligence (AI) as a fundamental enabling factor across multiple sectors. At the heart of the strategy is the ambition to achieve the goals of the "2000-watt Society" initiative by 2050, which requires a substantial reduction in per capita energy consumption and carbon emissions, while maintaining high living standards (Oyadeyi et al, 2025)[186]. In this context, AI is leveraged not as an isolated technological solution, but as an orchestrating intelligence capable of coordinating dynamic urban systems in real time.

The strategic pillars of Zurich's Smart City agenda are sustainability, resilience, inclusivity, and innovation (Stadt-zuerich.ch., 2024)[187]. More specifically, sustainability is pursued through the optimization of energy use within urban infrastructures and mobility networks, facilitated by predictive analytics and Machine Learning (ML) models. Resilience is strengthened through the use of AI to monitor critical urban resources and anticipate infrastructure risks, enabling proactive interventions that reduce the cost of more invasive repairs and ensure consistently high levels of safety and service provision. Inclusivity is rooted in Zurich's governance model, promoting citizen engagement through participatory platforms enhanced by data-driven insights. Finally, innovation is stimulated through strong partnerships between the public sector, private companies, and academic institutions, with the Swiss Federal Institute of Technology (ETH) and the Zurich University of Applied Sciences (ZHAW) being the most prominent examples of such collaborations. Practical examples include the ETH AI Center, a multidisciplinary research hub that brings together experts in computer science, engineering, and urban studies to foster innovation in AI applications for smart cities and sustainable mobility. This institute aims to develop data-driven urban solutions, working closely with the City of Zurich to create predictive models, real-time analytics, and optimization algorithms aimed at improving urban sustainability and operational efficiency (ETH AI Center, 2025)[188].

---

[186] Oyadeyi, O.A. and Oyadeyi, O.O. (2025). Towards Inclusive and Sustainable Strategies in Smart cities: a Comparative Analysis of Zurich, Oslo, and Copenhagen. *Research in Globalization*
[187] Stadt-zuerich.ch. (2024). Smart City
[188] ETH AI Center. (2025). AI in Retail & Smart Cities & Mobility

In collaboration with ZHAW, there is also the Smart Cities & Regions platform, which serves as a scientific partner in promoting the sustainable transformation of urban environments. Through this initiative, ZHAW engages in applied research projects, develops methodological frameworks, and designs training programs aimed at enhancing urban resilience and innovation. The platform facilitates the implementation of AI-based solutions in public services, mobility management, and energy optimization, contributing significantly to Zurich's strategic objectives for intelligent urban governance (ZHAW, 2025)[189].

Moreover, Zurich's Smart City strategy places strong emphasis on the ethical deployment of AI. The city adheres to fundamental principles such as transparency, accountability, and non-discrimination in the design and operation of algorithmic systems, ensuring that technological innovations align with the broader digital governance frameworks established by the Swiss Confederation (Stadt-zuerich.ch., 2024). In practical terms, this commitment translates into the systematic application of privacy-by-design protocols, public disclosure of algorithmic decision-making criteria, and the inclusion of bias mitigation mechanisms in AI models. These ethical guidelines are rigorously applied in critical public service sectors, such as smart mobility management systems and intelligent energy networks, where citizens' personal data and automated decision-making processes are directly involved. By institutionalizing these standards, Zurich strengthens public trust in smart city initiatives, ensuring that technological advancement is pursued in a socially responsible and legally compliant manner, thus eliminating barriers and concerns associated with the use of such systems (Stadt-zuerich.ch., 2024).

Zurich's approach to smart urban transformation demonstrates a clear shift from isolated smart city projects to an integrated urban ecosystem where AI-based services dynamically interact to achieve broad social objectives, thus interconnecting every aspect and function of urban life. This model has enabled Zurich to be recognized not only as a technological leader but also as a pioneer of sustainable, citizen-centred urban governance focused on well-being.

[189] ZHAW Zurich University of Applied Sciences. (2015)

3.2.2 AI-Driven Street Lighting Management and Mobility Optimisation

What has made and transformed Zurich into a smart city, especially in the context of Predictive Maintenance and Urban Optimization, is the way in which the city has not merely used Artificial Intelligence (AI) to improve mobility systems, but has extended such applications across a wide range of urban infrastructures, including public lighting networks, road and public transport vehicle maintenance, and the overall optimization of these resources, both monetary and otherwise, with the ultimate goal of consuming less, polluting less, and functioning better.

This holistic approach reflects the theoretical frameworks outlined in Chapter 2, where the dual role of AI in predictive maintenance and real-time operational optimization was highlighted as fundamental to the construction of sustainable and resilient urban environments. In Zurich, the intelligent management of traffic and street lighting infrastructures represents an integrated application of these principles: indeed, predictive models and IoT-based sensors enable continuous monitoring, dynamic adaptation, and optimization of resource use (Oyadeyi et al, 2025[190]; Stadt-zuerich.ch., 2024[191]). Looking more closely at the practical actions taken, in the field of mobility Zurich has implemented AI-based real-time traffic management systems to dynamically regulate traffic lights, redirect flows according to congestion patterns, and optimize public transport schedules. The "Verkehrsleitzentrale Zürich" (Zurich Traffic Control Centre) uses AI algorithms to analyze real-time traffic data collected from a wide network of IoT sensors installed across the city, allowing the system to dynamically adjust traffic signal cycles and issue real-time congestion alerts.

In terms of device figures, this includes more than 4,500 inductive sensors as of 2014 (Walker. A., 2025)[192], 470 traffic measurement stations (for both motorized and bicycle traffic) by 2025 (Kanton Zürich, 2025)[193], and BlipTrack Bluetooth Sensors, used to

[190] Oyadeyi, O.A. and Oyadeyi, O.O. (2025). Towards Inclusive and Sustainable Strategies in Smart cities: a Comparative Analysis of Zurich, Oslo, and Copenhagen. *Research in Globalization*
[191] Stadt-zuerich.ch. (2024). Smart City
[192] Walker. A. (2025). Zurich Installed 4,500 Street Sensors to Count Every Car in the City.
[193] Kanton Zürich. (2025). Verkehrsdaten.

monitor average travel times, installed along approximately 50 of the city's main roads since 2013 (Carstens, 2016)[194].

Europe Ranking 2024	World Ranking 2024	Urban Area	Hours Lost in 2024	Change from 2023	Change from 2022
1	5	**London**	101	2%	5%
2	6	**Paris**	97	0%	1%
3	15	**Dublin**	81	13%	14%
4	16	**Rome**	71	3%	4%
5	18	**Brussels**	74	9%	1%
6	20	**Warsaw**	70	15%	20%
7	24	**Milan**	64	7%	4%
8	26	**Rotterdam**	63	2%	7%
9	29	**Prague**	64	0%	14%
10	33	**Berlin**	58	5%	10%
11	34	**Bristol**	65	5%	-2%
12	36	**Utrecht**	63	-3%	3%
13	37	**Ljubljana**	67	14%	38%
14	38	**Leeds**	60	2%	0%
15	39	**Amsterdam**	55	0%	0%
16	40	**Manchester**	61	13%	13%
17	41	**The Hague**	58	0%	0%
18	42	**Munchen**	55	6%	-1%
19	43	**Budapest**	55	17%	-4%
20	44	**Lisboa**	60	5%	28%
21	47	**Stuttgart**	58	9%	13%
22	**48**	**Zurich**	**58**	**-3%**	**-4%**
23	49	**Cologne**	56	12%	16%
24	50	**Bath**	68	1%	-7%

Figure 40 - Smart City Index: Global Rankings and Performance Trends[195]

The results of these operations can be observed in the data on hours lost in traffic annually by drivers, which place Zurich as the 48th most congested urban area in the world and 22nd among European cities. While this position may not seem particularly favourable, especially when considering the relatively low number of car owners (only 4 out of 10

[194] Carstens, C.B. (2016). Smart Traffic Sensors Help Alleviate Traffic Congestion in Switzerland
[195] Source: personal reworking from INRIX (2025). Global Traffic Scorecard

residents own a vehicle)[196], it must be contextualized and compared to other cities on the list, where traffic time is generally increasing, whereas in Zurich this figure has been decreasing for several consecutive years (INRIX 2025)[197].

Secondly, Zurich has implemented an AI-based smart street lighting system that embodies the principles of predictive maintenance and energy optimization. Unlike traditional street lighting systems based on static schedules, Zurich's smart lights are equipped with IoT sensors that detect real-time environmental conditions, such as ambient light levels, the presence of pedestrians and vehicles, and even weather conditions. By processing data from the widespread city sensors in real time, AI algorithms autonomously adjust the brightness and operating schedules of the streetlights to minimize energy consumption without compromising safety. As discussed in Chapter 2.2.1, this application of predictive analytics not only reduces unnecessary energy consumption but also extends the operational life of lighting infrastructure, lowering maintenance costs and contributing to the city's broader goals, such as the 2000-watt society target (EWZ, 2024[198]; Sill Lighting, 2024[199]).

The integration of smart street lighting with traffic management is thus consistent with the theoretical models previously presented, where smart cities are conceptualized as interconnected ecosystems requiring multi-infrastructure optimization. In this context, Zurich can indeed be considered a prime example of how such technologies can effectively move from mere theory to concrete application. Adaptive street lighting management is not marginal to mobility challenges: efficient lighting influences pedestrian safety, bicycle commuting, and even traffic flow during nighttime hours, all of which are essential components of an efficient, citizen-centred mobility system (Oyadeyi et al., 2025).

By combining AI-based traffic control and adaptive street lighting, Zurich exemplifies how cities can transcend isolated interventions toward a fully integrated, data-driven urban management system. This strategic alignment between energy efficiency, infrastructure

[196] Office, F.S. (2024). Road vehicles - Stock, level of motorisation
[197] INRIX (2025). *Global Traffic Scorecar*
[198] ewz. (2024). 2,000-watt society | Our commitment | ewz
[199] Sill Lighting. (2024). Intelligent city lighting, Zurich | Sill Lighting

resilience, and transport optimization demonstrates the practical feasibility of the smart city principles outlined in the previous chapters.

3.2.3 Technologies Used: IoT, Digital Twins, Adaptive Algorithms

The architecture and structure of smart cities is, and must be by definition as previously anticipated, supported by a complex technological framework composed of interconnected sensors, simulation environments, and adaptive computational models.

Indeed, it is through these elements that the predictive analytics and optimization frameworks discussed in Chapter 2 can be operationalised, translating theory into the everyday practice of urban management.

The implementation of Internet of Things (IoT) devices is widespread across Zurich's mobility systems and public services. As previously discussed, approximately 4,500 inductive loop sensors are integrated into the city's road network to collect real-time data on vehicle volume, speed, and lane occupancy. In addition, traffic monitoring stations and BlipTrack Bluetooth sensors monitor average travel speed (Walker. A., 2025[200], Kanton Zürich, 2025[201], Carstens, 2016[202]).

These data are used by the city's Traffic Management Centre to regulate traffic signal timing and improve flow based on real-time models rather than traditional static schedules (Walker. A., 2025), which rely on outdated technologies that have not evolved significantly over the last decades.

Similar technologies are employed in motion sensors for lighting activation and brightness regulation. Interestingly, in some cases these sensors adapt not only to movement, but also to volume, time of day, and weather conditions, maximizing the efficiency of resource usage (Sill Lighting., 2024)[203].

As for digital twins, these are used in Zurich in collaboration with academic research centres such as ETH Zurich and ZHAW to support complex urban scenario simulations, predictive infrastructure planning, and dynamic evaluation of public policies. The

[200] Walker. A. (2025). Zurich Installed 4,500 Street Sensors to Count Every Car in the City.
[201] Kanton Zürich. (2025). Verkehrsdaten.
[202] Carstens, C.B. (2016). Smart Traffic Sensors Help Alleviate Traffic Congestion in Switzerland
[203] Sill Lighting. (2024). Intelligent city lighting, Zurich | Sill Lighting

operational principle of these models is based on the creation of high-fidelity virtual representations of urban components, such as streets, buildings, or energy networks, fed in real time by data from IoT networks (ETH AI Centre., 2025)[204]. This enables the anticipatory evaluation of the effects of structural or regulatory interventions, reducing uncertainty and decision-making risks, and making it possible, for example, to assess structural erosion, necessary repairs, or responses to various types of natural disasters or social events in specific locations and conditions.

A concrete application can be observed in the congestion simulation project at the Zurich Verkehrsleitzentrale, where digital twins are used to replicate traffic behaviour under exceptional conditions, such as accidents or public events. These simulated scenarios allow testing of the road network's response to different detour strategies and signal optimization methods, thereby improving operational resilience (Schrotter, G. et al, 2020)[205]. Similarly, ETH Zurich has applied the logic of digital twins to energy management in public buildings, such as municipal schools, integrating meteorological and behavioural data to optimize HVAC (heating, ventilation, and air conditioning) systems based on actual occupancy, achieving energy savings compared to standard regulation (ETH AI Centre, 2025).

In parallel, the city's adaptive control systems leverage AI-based algorithms that process real-time multivariate data streams from environmental sensors, infrastructure, and mobile applications used by citizens. These algorithms not only respond to current conditions but also learn over time, continuously updating their parameters to anticipate urban network behaviours. In mobility, for example, public transport scheduling is optimized through predictive models that estimate demand based on events, weather forecasts, and seasonal variations, allowing the system to proactively adjust service frequency and capacity. Furthermore, critical intersections are managed by intelligent signalling systems that dynamically prioritize vehicles (e.g., ambulances, trams, buses), reducing transit time along main corridors (Stadt Zürich, 2024)[206].

---

[204] ETH AI Center. (2025). AI in Retail & Smart Cities & Mobility

[205] Schrotter, G. and Hürzeler, C. (2020). The Digital Twin of the City of Zurich for Urban Planning. PFG, Journal of Photogrammetry, Remote Sensing and Geoinformation Science

[206] Stadt-zuerich.ch. (2024). Smart City

Regarding infrastructure maintenance, Zurich employs predictive algorithms that assess the structural degradation of roads, electrical systems, and water networks based on historical failure data, environmental conditions, and actual usage. This enables automatic activation of preventive interventions when specific risk or performance thresholds are exceeded, moving beyond traditional fixed-interval approaches (Lehtola et al, 2022)[207]. For example, if a structure is known to be particularly sensitive to a given weather event, and such an event occurs repeatedly within a short timeframe, sensors would detect and anticipate a potential structural crisis, triggering alerts and initiating pre-emptive maintenance (Abhilash, 2024)[208].

The technological integration of IoT networks, virtual simulation through digital twins, and adaptive decision-making logic constitute the digital backbone of Zurich's intelligent urban governance and are the very definition of how a traditional city can truly become a smart city. These systems are not only functionally distinct, but also interdependent, forming an integrated feedback loop that enables the city to monitor, analyze, and optimize its core infrastructure resources with high temporal and spatial resolution (Lehtola et al, 2022; Abhilash, 2024).

3.2.4 Results and Performance Metrics

Zurich's leadership in the 2025 Smart City Index, where it ranks first among 146 global cities, is the result of a solid, data-driven approach to urban innovation. The city has consistently scored highly across the three key performance dimensions evaluated by the index: infrastructure, technology, and citizen-centred services. These results therefore reflect the operational maturity and commitment of Zurich's urban systems integrated with Artificial Intelligence (AI), confirming the theoretical potential of smart infrastructures discussed in Chapter 2 (IMD, 2025)[209].

---

[207] Lehtola, V.V., Koeva, M., Elberink, S.O., Raposo, P., Virtanen, J.-P., Vahdatikhaki, F. and Borsci, S. (2022). Digital twin of a city: Review of technology serving city needs. International Journal of Applied Earth Observation and Geoinformation

[208] Abhilash (2024). Empowering Zurich: How IoT Solutions Are Driving Smart City Success. [online] Intertoons Zurich

[209] IMD. (2025). IMD_Smart_City_2025_Report.pdf

Focusing on structural performance, Zurich scores particularly high in areas related to health, mobility, and governance. Specifically, residents report that basic healthcare and sanitation needs are adequately met, reaching a score of 84.7, while with 74.4 public safety is perceived as non-problematic, and air pollution is rarely cited as a major concern (66.1). These indicators suggest that Zurich's infrastructural foundations are stable and inclusive, providing a favourable environment for the successful implementation of AI-enhanced services (IMD, 2025).

Category	Indicator	Score
Mobility	Public transport is satisfactory	80.8
	Traffic congestion is not a problem	41.5
Governance	Residents contribute to decision-making of local government	75.2
	Residents provide feedback on local government projects	71.8
	Information on local government decisions is easily accessible	73.5
	Corruption of city officials is not an issue of concern	64.7
Health & Safety	Air pollution is not a problem	66.1
	Recycling services are satisfactory	85.6
Activities	Green spaces are satisfactory	75.3

Figure 41 - Key Structure Indicator in Zurich[210]

Regarding the mobility sector, Zurich presents a heterogeneous profile. While public transport satisfaction is high (80.8), residents believe traffic congestion is quite an issue (with a score for not being a problem of only 41.5), although, as discussed in previous sections, congestion is fortunately declining. This discrepancy nevertheless highlights the continued need for AI-based traffic optimization, including dynamic signal control and

[210] Source: personal reworking from IMD. (2025). IMD_Smart_City_2025_Report.pdf

predictive vehicle flow modelling. That said, technology applications aimed at improving mobility are clearly in place: for example, with a score of 62.8, residents state that mobile apps provide useful traffic information, and with 53.8 that bike-sharing systems have helped alleviate congestion (IMD, 2025).

Category	Indicator	Score
Mobility	Online scheduling and ticket sales ease public transport use	78.9
	City provides traffic info via mobile phones	62.8
	Bicycle hiring has reduced congestion	53.8
	Apps for parking have reduced journey time	47.5
	Car-sharing apps have reduced congestion	44.7
Governance	Processing ID documents online has reduced waiting times	63.7
	Online platform for civic proposals has improved city life	56
	Online voting has increased participation	53.8
	Open data on finances has reduced corruption	50.4
Opportunities	Internet speed and reliability meet city needs	81.2
	Online access to job listings facilitates employment	78.3
	Municipal online services facilitate business creation	59.2
	IT skills taught well in schools	63.7

Figure 42 - Key Technology Indicators[211]

[211] Source: personal reworking from IMD. (2025). IMD_Smart_City_2025_Report.pdf

On the technological front, Zurich receives the highest possible rating (AAA) among the 146 cities, with particularly strong performance in areas such as digital access to public services and smart healthcare solutions. For instance, the city's digital platforms are positively rated by respondents for supporting job searches (78.3) and business creation (59.2). As for public service bookings, the score of 63.9 confirm that medical appointments can be efficiently scheduled online, and citizen agree that reporting urban maintenance issues online provides a rapid solution (59). These results indicate that AI and digital platforms are not only improving administrative efficiency but are also strengthening Zurich's socioeconomic resilience (IMD, 2025).

Zurich's achievements in energy efficiency are also notable. The city continues to reduce per capita energy consumption in line with its 2000-watt society goal. AI-based systems contribute to this progress through smart lighting, public service demand forecasting, and real-time energy network monitoring. Although this specific index does not quantify energy savings, these efforts are supported by previous performance assessments, which estimated up to a 70% reduction in street lighting energy consumption thanks to adaptive systems (SILL Lighting, 2023[212]; Terra, L., 2024[213]).

Performance is also assessed through citizen feedback mechanisms integrated into smart governance. According to the IMD survey, Zurich residents believe they can provide feedback on local government projects (71.8), and they state that online participation has improved their civic engagement (score of 62.7). These data reinforce the importance of inclusive digital governance structures that leverage AI not only for efficiency, but also for transparency and citizen empowerment (IMD, 2025).

Overall, these performance parameters confirm Zurich's ability to translate its technological investments into concrete and measurable results, ensuring in most cases high levels of citizen satisfaction, arguably one of the most important indicators of a city's functionality.

[212] Sill Lighting. (2024). Intelligent city lighting, Zurich | Sill Lighting

[213] Terra, L. (2024). Smart city -La città 'intelligente' del futuro

3.2.5 Challenges and Future Prospects

As both Zurich's residents and its own governance structures are aware, and despite its status as a global leader in smart city performance, the city continues to face a number of persistent challenges that reflect both the complexity of technological urban governance, and the socio-political trade-offs associated with AI integration. These challenges mirror the theoretical risks discussed in Chapter 2, particularly those related to privacy, algorithmic transparency, and inclusive digital participation.

According to the scores provided by the city's own residents, one of the most significant operational challenges lies in managing urban traffic congestion. Although Zurich has made remarkable progress in optimizing public transport, survey data report a score of only 41.5/100, indicating that most residents consider traffic congestion an unresolved issue (IMD, 2025)[214]. This underscores the need to strengthen AI-based traffic forecasting and multimodal integration through Mobility-as-a-Service (MaaS) platforms, as outlined earlier in Section 2.3.4, and above all to further optimize public services to replace the still widespread use of private vehicles.

In terms of digital governance, ensuring equitable access to smart services remains a central concern for every citizen. Although Zurich excels in offering online services and fostering digital civic engagement, the scores reported in these categories indicate that there is still room for improvement in online participation opportunities (IMD, 2025). This reveals a digital inclusion gap that must be addressed through targeted awareness initiatives, enhanced accessibility, and participatory design frameworks, precisely because, as stated in Section 2.5.3, the failure to integrate inclusivity into AI governance risks reinforcing existing inequalities in access to public services and decision-making power.

From a technological standpoint, the integration of advanced AI systems, particularly those used in adaptive mobility and infrastructure diagnostics, continually raises questions regarding data ethics, transparency, and cyber-resilience. However, it is also important to consider that the majority of Zurich residents (65.9%) report being willing to share personal data in exchange for improved mobility and traffic optimization (IMD,

[214] IMD. (2025). IMD_Smart_City_2025_Report.pdf

2025). Nevertheless, the city must continue to uphold and clearly communicate high standards of data protection and algorithmic accountability, ultimately to preserve the trust and willingness of its citizens. It is therefore evident that the balance between optimization and surveillance is delicate and requires clear regulatory frameworks and ethical oversight mechanisms, as discussed in Section 2.5.2.

Looking ahead, Zurich's prospects, in continuity with recent years, rest on the ongoing evolution of its smart infrastructure ecosystem, consistently investing and progressing by listening to resident feedback and addressing areas for improvement. Advancement opportunities include broader implementation of digital twins for urban simulation and the scaling of AI-based maintenance platforms across the city, as well as continuing to develop and strengthen partnerships with academic centres of excellence such as ETH and ZHAW, a relationship that serves as a replicable model for other cities seeking to combine scientific rigour with practical implementation (Esri, 2025)[215].

All these procedures and developments share the overarching goal of achieving the already discussed "2000-watt society" by 2050, which requires placing special focus on the city's energy policies and efficiency initiatives.

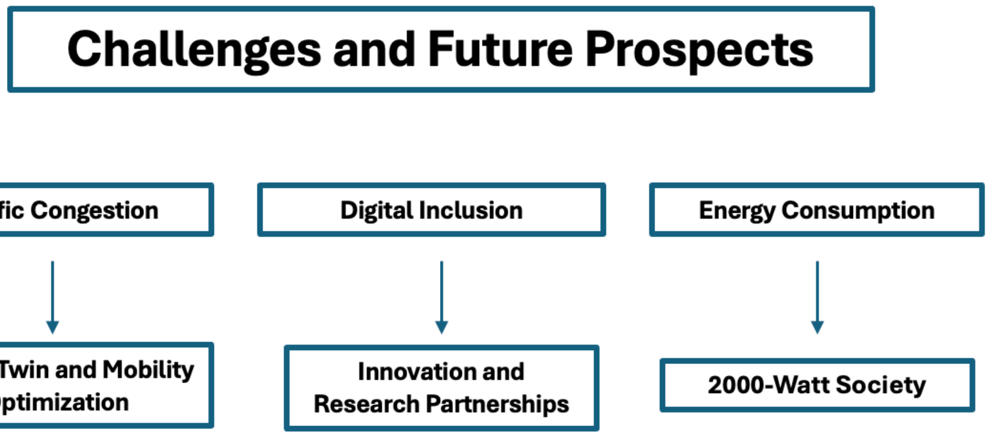

Figure 43 - Challenges and Future Prospects[216]

Internationally, Zurich's intelligent governance model offers significant potential for adaptation in other urban contexts, especially those facing similar resource constraints

[215] Esri. (2025). Video: Inside Zurich's Digital Twin for Infrastructure Management
[216] Source: personal elaboration

or sustainability targets. This makes the city’s commitment to continuous monitoring, citizen feedback, and iterative system refinement a compelling case for dynamic scalability. However, any attempt to replicate Zurich’s success must consider contextual factors such as institutional capacity, digital maturity, and citizen trust, which provide the continuous feedback and data availability necessary to achieve such goals.

3.3 Key Learnings and Implementation Insights

In conclusion, the case of Zurich offers significant insights into the conditions that enable the successful integration of Artificial Intelligence (AI) in complex urban systems. Its case in particular illustrates the transition from isolated smart solutions to a coordinated digital ecosystem, structured around strategic goals, institutional collaboration, and continuous performance monitoring within a balanced and supervised system that continues to improve and refine itself day by day.

A central element of Zurich’s success lies in the robustness of its governance architecture, which supports structured cooperation between the municipal administration, academic research institutions, and the private sector. Indeed, as described multiple times, the city’s long-standing collaboration with ETH Zurich and ZHAW has provided both the technical expertise and analytical capacity needed to plan and implement advanced AI-based systems that continue to evolve and design new avenues for application and improvement.

Zurich’s progress is also attributed to its ability to integrate technological initiatives into a coherent strategic vision. A clear example of this is the city’s commitment to the 2000-watt society goal, which serves as a unifying framework guiding technological innovation towards clearly defined sustainability objectives. This long-term orientation has ensured that digital tools are employed not only for efficiency but also in service of broader environmental and social goals.

Another key insight that emerges from Zurich’s model is the capacity of AI to deliver measurable improvements in urban operations when combined with real-time data collection and adaptive algorithmic logic. This is evident in the implementation of smart lighting networks and dynamic traffic control systems, which have led to significant reductions in energy consumption and traffic congestion, while predictive maintenance has improved service continuity and cost efficiency, results clearly perceived by the city's residents. These outcomes support the theoretical arguments presented in Chapter 2 regarding the operational value of real-time optimization and predictive analytics in smart cities.

However, it is important to recognize that Zurich's experience, alongside its outstanding results and ambitious future goals, also highlights persistent challenges. Issues related to digital equity and participatory governance remain critical, and although digital services in Zurich are widely accessible, their impact on civic engagement appears more modest. This suggests that digital tools must be accompanied by active strategies to promote engagement, trust, and inclusivity, particularly among disadvantaged population groups.

The replicability of Zurich's model in other urban contexts depends on the presence of various enabling conditions, including institutional capacity, a high level of digital maturity, and a governance culture open to innovation and evaluation. Equally important is citizen trust in government policies and the belief that the sacrifices made will lead to tangible results. It is therefore crucial to remember that although advanced infrastructures and AI implementation are important, they are not sufficient without parallel investments in citizen-centred design, ethical oversight, and transparent data governance.

Chapter 4 - A Personal Analysis of the Inhabitants' Considerations

4.1 Purpose of the Survey

In order to integrate an empirical perspective into the theoretical framework developed in the previous chapters, a survey was conducted to gather opinions, perceptions, and attitudes of citizens regarding the adoption of Artificial Intelligence (AI) in urban contexts. The primary objective of the investigation was to understand the level of awareness, acceptance, and willingness toward the use of intelligent technologies in city management, with specific reference to public services, mobility, energy efficiency, and urban governance.

The questionnaire specifically explored individuals' willingness to share their personal data in exchange for tangible improvements in urban services and, consequently, in their daily lives. This aspect was considered in close relation to the level of trust placed in local institutions and their ability to manage advanced technological systems in an ethical, secure, and transparent manner. A further area of investigation concerned the perceived impact of AI on urban quality of life. The survey aimed to determine whether citizens view the introduction of AI as an opportunity for progress or, conversely, as a source of potential risks, inequalities, or loss of control, and especially which domains they believe these technologies should be most applied to.

The aim of the survey is therefore twofold: on the one hand, to provide empirical evidence to support the theoretical reflections developed in the preceding chapters; on the other, to highlight the key factors influencing social acceptance of AI in urban contexts, thereby offering insights useful for guiding future implementation strategies in a participatory, inclusive, and sustainable direction.

4.2 Methodology and Sample

Regarding the sample, the reference population includes residents of Zurich (the city analysed in the case study), London (the highest-ranked European metropolis in the IMD Smart City Index 2025), and Rome (the city of residence and context of thesis development), for a total of approximately 13 million inhabitants as of 2025. Assuming a 90% confidence level with a margin of error of 6,5%, the required sample size was calculated to be approximately 150 respondents, proportionally distributed according to the population size of each city.

The survey was administered online in April 2025, using a Google Form distributed via social media and contacts in the cities of interest. A total of 151 responses were collected, primarily from individuals aged between 21 and 35, who completed a questionnaire composed of 14 questions designed to collect quantitative data in a rapid and direct manner with the possibility of inserting comments to each question.

4.3 Main Survey Results

The analysis of the survey results clearly reveals a strongly positive attitude among the population toward Artificial Intelligence (AI) and its application within smart cities. In fact, 93% of respondents expressed support for the integration of AI in urban contexts, recognising its potential as a tool for improving public services. This reflects a high level of openness to technological innovation and indicates growing collective interest in the digital transformation of urban spaces.

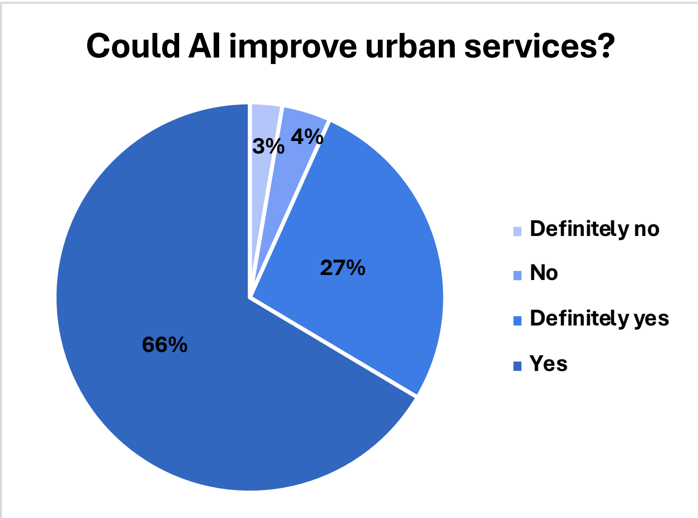

Figure 44 - Could AI improve urban services?[217]

One particularly noteworthy aspect emerging from the survey concerns the prioritisation of different application domains for intelligent technologies. The responses show a

[217] Source: personal reworking from poll drafted by the candidate

relatively homogeneous preference pattern, with a clear majority (90%) indicating "mobility and traffic" as the top priority. This was followed by "energy and environment" (71%) and "waste management" (68%), demonstrating that citizens clearly identify the areas in which AI can generate a tangible and immediate impact. It is important to note that these preferences were expressed without participants being previously informed of the current state of AI deployment, confirming the alignment between perceived societal needs and the most actively developing technological domains.
With regard to the daily use of AI-based tools, the data reveal that, although one third of respondents reported not being fully aware of which systems utilise such technologies, 89% stated that they use applications involving AI, such as Google Maps, Waze, Uber, FreeNow, or Lime, on a daily or very frequent basis. Furthermore, 81% of users considered these applications not only useful but largely essential for managing everyday life, confirming the pervasiveness and integration of AI into the urban experience.

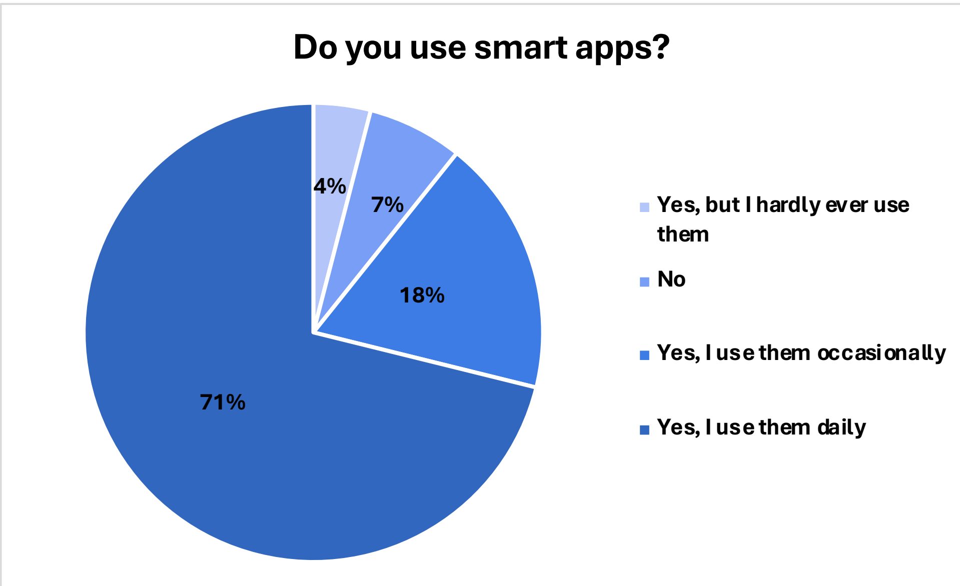

Figure 45 - Do you use smart apps?[218]

One of the theoretical issues addressed in the earlier chapters that received direct confirmation through the survey concerns privacy and the management of personal data. The results depict a complex yet generally open stance toward data sharing, provided that

[218] Source: personal reworking from poll drafted by the candidate

adequate guarantees are in place. Only 4% of respondents were entirely opposed to the sharing of personal data, while 50% expressed conditional willingness, contingent on anonymity and privacy protection. An additional 36% considered it essential that data usage be limited strictly to public purposes and the common good. Lastly, 10% were willing to share their data without any particular restrictions.

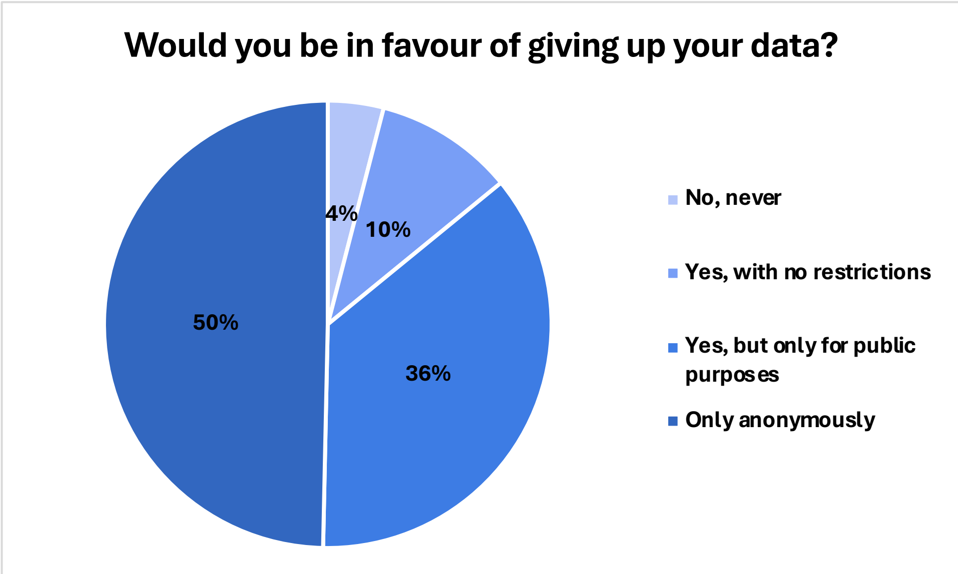

Figure 46 - Would you be in favour of giving up your data?[219]

These findings support conclusions drawn from the theoretical literature: resistance to widespread adoption of intelligent technologies is not insurmountable but can be mitigated through the strengthening of trust between public institutions and citizens, based on transparency and assurance that data will be used responsibly and ethically.

Nonetheless, while a general willingness to share data is evident, the results also underscore a strong demand for transparency in automated decision-making processes. In fact, 20% of respondents deemed it important, and 77% considered it essential, to know with certainty when an administrative decision is made by an AI system rather than by a human authority. This highlights the need for clear communication mechanisms and traceability in the adoption of AI within urban governance, reflecting the necessity of systems that make the origin of impactful decisions explicit to the public.

[219] Source: personal reworking from poll drafted by the candidate

Finally, one of the final questions of the survey aimed to assess the extent to which smart technologies influence individuals' preferences regarding where to live. Seventy-two% of respondents stated that the presence of smart city features would represent a decisive factor in the event of relocation or city selection. An additional 6% acknowledged that such aspects would have some influence, though not decisive, while only 22% indicated that these elements would not affect their decision.

The conclusions drawn from these findings reinforce the notion that AI is rapidly becoming an integrated component of urban life and contemporary culture. The majority of respondents demonstrated a clear awareness of the importance of embracing emerging technologies, with an attitude oriented not only toward individual benefit but also toward the improvement of collective well-being. This outlines a scenario in which the adoption of AI in cities is no longer a futuristic hypothesis but a continuously evolving reality. However, such development requires a responsible, inclusive, and transparent approach in order to be fully accepted and effectively leveraged.

Conclusion

This thesis aims to investigate the role of Artificial Intelligence (AI) in the transformation of business operations and, more specifically, how such developments, changes, and improvements can have a significant impact on everyday life, particularly through their application in urban management systems and smart cities. Through an interdisciplinary and multi-level approach, the research aimed to explore how AI contributes not only to process optimisation and predictive capabilities but also to the advancement of sustainability, efficiency, and inclusiveness goals within contemporary urban environments. These assumptions were based on a theoretical and technological framework, understanding and analysing the evolution of AI from early rule-based systems to current paradigms of Machine Learning (ML) and Deep Learning (DL), allowing us to understand the direction in which technology and research are heading.

By analysing its integration in business operations, the study highlighted how AI enables real-time decision-making, resource optimisation, and the automation of complex processes. Particular emphasis was placed on the transformative role of digital twins and generative models in operational contexts, highlighting their potential in supporting strategic planning and the continuous improvement of performance. The aim of the theoretical analysis was to understand how these concepts could be extended to the urban context by examining the applications of AI in smart cities. This section demonstrated that the effectiveness of AI in urban environments is closely linked to its capacity to enable proactive infrastructure management, reduce systemic inefficiencies, and improve the delivery of public services. Predictive maintenance and the optimisation of urban mobility were identified as key areas in which AI-generated insights can bring substantial benefits, including cost reduction, emission control, and greater citizen satisfaction.

However, it was also important to pay attention to the challenges associated with the large-scale implementation of AI, particularly those relating to governance, data ethics, and digital inequality. It was interesting to observe how such theoretical aspects have already been partially applied in urban contexts such as Zurich, which was chosen as the subject of a detailed case study, allowing the application of the theoretical framework to an empirical context. Zurich is, in fact, recognised as a global benchmark in the development of smart cities, exemplifying how AI technologies, from IoT sensor networks to adaptive algorithms and digital twins, can be successfully integrated into urban systems.

The main point highlighted is that Zurich's solid performance is based on a long-term strategic vision, inter-institutional cooperation, and a commitment to ethical and inclusive digital governance. These are all foundational pillars considered essential to achieving the objectives addressed and outlined in this analysis. However, some limitations persist in Zurich, particularly in areas such as traffic congestion mitigation and accessibility to participatory digital platforms. These results confirm that even in cases where the technological infrastructure is already advanced and continuously evolving, there is still ample room for improvement in terms of implementation and tangible impact on citizens, which means that even those contexts considered highly advanced and to be taken as examples still have a long way to go in achieving the goals and possibilities that such technologies have to offer.

Among the most surprising aspects highlighted by this analysis are the results obtained through an empirical perspective via the analysis of a survey conducted to assess public perception, awareness, and attitudes towards AI adoption in urban contexts. The results confirmed a broadly positive perspective towards the integration of technologies in cities: 93% of respondents expressed support for the future use of AI in smart cities, particularly as a tool to improve urban services, identifying mobility and traffic management, energy and environment, and waste management as the most critical are as where AI systems should be implemented. Moreover, while over a third of participants stated they had limited knowledge of AI, nearly 89% reported using AI-based applications daily, and the vast majority considered them extremely useful or essential.

The most surprising results, however, concerned data sharing. According to current literature, data management is one of the greatest challenges facing the diffusion of AI. However, according to the analysed survey, only 4% of respondents declared themselves completely opposed, while the majority were in favour of data use provided anonymity was guaranteed (50%) and/or the data were used exclusively for public benefit (36%).

These results highlight the importance of trust in public institutions and the need for transparent data governance, as it becomes clear that citizens are not opposed to data sharing in itself, since they would be willing to share them for the common good and the improvement of their city, but rather that it is necessary to establish a relationship of trust and guarantees with institutions.

Transparency in governance is and will continue to be important: specifically, 97% of respondents considered it important or essential to know whether administrative decisions are made by AI systems or by human authorities, underlining the need for algorithmic transparency. Furthermore, 72% indicated that the technological progress of a city would be a decisive factor in choosing where to live, further demonstrating the social relevance of technologies for smart cities.

In conclusion, this study confirms that Artificial Intelligence has gone beyond the experimental phase and is becoming a central pillar in the evolution of both business and urban systems, and that citizens are both directly and indirectly aware of this transformation. The combined theoretical and empirical evidence demonstrates the transformative potential of AI when implemented responsibly, transparently, and with the active involvement of citizens. However, the path towards inclusive and effective smart cities also requires parallel investments in digital literacy, ethical oversight, and participatory governance. Only by aligning technological innovation with social values can AI truly serve the public interest and contribute to a resilient, efficient, and equitable urban future. Moreover, based on the data and opinions expressed by residents, it is clear and indisputable that such systems, if implemented correctly and in line with commitments made to citizens, have the potential to radically transform urban life, significantly improving residents' quality of life while not increasing, and in many cases even reducing, the operational costs of managing the city.

Additionally, from a business and investment perspective, these technologies and infrastructures appear to be among the most promising methods for future growth. On one hand, research and development are highly active; on the other, the cities and contexts applying such technologies still have substantial room for growth, leaving vast spaces for improvement and investment.

References

Abbasi, M., Nishat, Rahnuma Islam, Bond, C., Graham-Knight, J.B., Lasserre, P., Lucet, Y. and Najjaran, H. (2024). *A Review of AI and Machine Learning Contribution in Predictive Business Process Management* (Process Enhancement and Process Improvement Approaches). [online] arXiv.org. Available at: https://arxiv.org/abs/2407.11043.

Abhilash (2024). *Empowering Zurich: How IoT Solutions Are Driving Smart City Success*. [online] Intertoons Zurich. Available at: https://www.intertoons.ch/post/empowering-zurich-how-iot-solutions-are-driving-smart-city-success.

Abu Dhabi Media Office (2025). *Abu Dhabi ranks 5th globally in 2025 IMD Smart City Index*. [online] Mediaoffice.abudhabi. Available at: https://www.mediaoffice.abudhabi/en/infrastructure/abu-dhabi-ranks-5th-globally-in-2025-imd-smart-city-index/

Adepoju, O.D., Tijani, B. and Karera, S. (2024). *Artificial Intelligence Skepticism in Career Domains*. International Journal for Digital Society, 15(1), pp.1880–1888. https://doi.org/10.20533/ijds.2040.2570.2024.0236

Ai, G., Zuo, X., chen, G. and Wu, B. (2021). *Deep Reinforcement Learning based Dynamic Optimisation of Bus Timetable*. [online] arXiv.org. Available at: https://arxiv.org/abs/2107.07066.

AL-Dabbagh, R. (2022). *Dubai, the sustainable, smart city. Renewable Energy and Environmental Sustainability*. doi:https://doi.org/10.1051/rees/2021049.

Alanne, K. and Sierla, S. (2022). A*n overview of machine learning applications for smart buildings*. Sustainable Cities and Society. doi: https://doi.org/10.1016/j.scs.2021.103445.

Almeida, F. and Carneiro, P. (2023). *Perceived Importance of Metrics for Agile Scrum Environments*. Information, [online]. doi: https://doi.org/10.3390/info14060327.

Amin, I. (2025). AlphaBOLD. [online] Microsoft Dynamics and NetSuite Partner & Dynamics CRM Consultants in San Diego. Available at: https://www.alphabold.com/ai-powered-predictive-maintenance-in-manufacturing/.

Atommobility.com. (2024). *How is AI transforming the micromobility industry?* [online] Available at: https://www.atommobility.com/blog/how-is-ai-transforming-the-micromobility-industry.

Basal, M., Saraç, E. and Özer, K. (2024). Dynamic Pricing Strategies Using Artificial Intelligence Algorithm. Open Journal of Applied Sciences, [online] 14(08), pp.1963–1978. doi: https://doi.org/10.4236/ojapps.2024.148128.

Batty, M., Axhausen, K.W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G. and Portugali, Y. (2012). *Smart cities of the future. The European Physical Journal Special Topics*, [online]. doi: https://doi.org/10.1140/epjst/e2012-01703-3.

Ben Slama, A., Mouelhi, A., Sahli, H., Manoubi, S., Mbarek, C., Trabelsi, H., Fnaiech, F. and Sayadi, M. (2017). *A new preprocessing parameter estimation based on geodesic active contour model for automatic vestibular neuritis diagnosis.* Artificial Intelligence in Medicine. doi:https://doi.org/10.1016/j.artmed.2017.07.005.

Best Practice AI. (2016). *AI Case Study | Deutsche Bahn reduces maintenance cost by 25% and delay-causing failures using machine learning*. [online] Available at: https://www.bestpractice.ai/ai-case-study-best-practice/deutsche_bahn_reduces_maintenance_cost_by_25%25_and_delay-causing_failures_using_machine_learning.

Bodemer, O. (2024). *Revolutionising Finance: The Impact of AI and Cloud Computing in the Banking Sector*. [online] ResearchGate. Available at: https://www.researchgate.net/publication/378704632_Revolutionising_Finance_The_Impact_of_AI_and_Cloud_Computing_in_the_Banking_Sector.

Bunte, A., Richter, F. and Diovisalvi, R. (2021). *Why It is Hard to Find AI in SMEs: A Survey from the Practice and How to Promote It. Proceedings of the 13th International Conference on Agents and Artificial Intelligence*. https://doi.org/10.5220/0010204106140620

Cai, K. (2025). *Verizon says Google AI for customer service agents has led to sales jump*. Reuters. [online] 9 Apr. Available at: https://www.reuters.com/technology/verizon-says-google-ai-customer-service-agents-has-led-sales-jump-2025-04-09/.

Cambria, E. and White, B. (2014). *Jumping NLP Curves: A Review of Natural Language Processing Research* [Review Article]. IEEE Computational Intelligence Magazine, [online]. doi: https://doi.org/10.1109/mci.2014.2307227.

Camus, A. (2022). *City of Helsinki Expands Digitalization with Citywide Digital Twin - Engineering.com*. [online] Engineering.com. Available at: https://www.engineering.com/city-of-helsinki-expands-digitalization-with-citywide-digital-twin/

Cappelli, P., Tambe, P. and Yakubovich, V. (2019). *Artificial Intelligence in Human Resources Management: Challenges and a Path Forward*. SSRN Electronic Journal, [online]. doi:https://doi.org/10.2139/ssrn.3263878.

Carstens, C.B. (2016). *Smart Traffic Sensors Help Alleviate Traffic Congestion in Switzerland*. [online] Available at: https://www.linkedin.com/pulse/smart-traffic-sensors-help-alleviate-congestion-carstens/.

Cavoukian, A. (2010). *Privacy by design: the definitive workshop*. A foreword by Ann Cavoukian, Ph.D. Identity in the Information Society. doi: https://doi.org/10.1007/s12394-010-0062-y.

Chadalavada, S., Faust, O., Salvi, M., Seoni, S., Raj, N., Raghavendra, U., Gudigar, A., Barua, P.D., Molinari, F. and Acharya, R. (2024). *Application of artificial intelligence in air pollution monitoring and forecasting: A systematic review*. Environmental Modelling & Software, [online] . doi: https://doi.org/10.1016/j.envsoft.2024.106312.

Choi, T.-M., Wallace, S.W. and Wang, Y. (2018). *Big Data Analytics in Operations Management*. Production and Operations Management, 27(10), pp.1868–1883. doi: https://doi.org/10.1111/poms.12838.

Chow, A.R. (2024). *How AI Is Making Buildings More Energy-Efficient*. [online] TIME. Available at: https://time.com/7201501/ai-buildings-energy-efficiency/.

Chowdhary, K.R. (2020). *Natural Language Processing. Fundamentals of Artificial Intelligence*. doi: https://doi.org/10.1007/978-81-322-3972-7_19.

Chui, M., Francisco, S., Manyika, J., San, Mehdi, F., Chicago, M., Henke, N. and London (2018). *NOTES FROM THE AI FRONTIER INSIGHTS FROM HUNDREDS OF USE CASES*. [online] Available at: https://www.mckinsey.com/westcoast/~/media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Notes%20from%20the%20AI%20frontier%20Applications%20and%20value%20of%20deep%20learning/Notes-from-the-AI-frontier-Insights-from-hundreds-of-use-cases-Discussion-paper.pdf.

Clatworthy, B. (2024). *Hi-tech traffic lights could give cyclists the priority over cars*. [online] Thetimes.com. Available at: https://www.thetimes.com/uk/transport/article/traffic-lights-that-prioritise-cyclists-over-cars-to-be-trialled-rv3hqztwx?region=global.

Cohen, G. (2022). *Algorithmic Trading and Financial Forecasting Using Advanced Artificial Intelligence Methodologies*. Mathematics, [online]. doi: https://www.mdpi.com/2227-7390/10/18/3302

Crespi, N., Drobot, A. and Minerva, R. (2023). The Digital Twin: What and Why? Springer eBooks. doi: https://doi.org/10.1007/978-3-031-21343-4_1.

Camarella, S., Conway, M., Goering, K., Huntington, M. (2024). *Transforming Digital twins: The next frontier of factory optimization* | McKinsey. [online] Available at:

Deloitte (2022). P*redictive Maintenance and The Smart Factory*. [online] Deloitte United States. https://www2.deloitte.com/us/en/pages/operations/articles/predictive-maintenance-and-the-smart-factory.html.

Deloitte Insights, 2024, *AI-Driven Process Automation: Unlocking Enterprise Efficiency*, Deloitte Review, https://www2.deloitte.com/insights

Dilda, V., Mori, L., Noterdaeme, O. and Schmitz, C. (2017). *Manufacturing: Analytics unleashes productivity and profitability* | McKinsey. [online] www.mckinsey.com. Available at: https://www.mckinsey.com/capabilities/operations/our-insights/manufacturing-analytics-unleashes-productivity-and-profitability.

Dipartimento per la trasformazione digitale. (n.d.). *Mobility as a Service for Italy*. [online] Available at: https://innovazione.gov.it/progetti/mobility-as-a-service-for-italy/.

Docdigitizer. (2023). N*atural Language Processing (NLP) for Document Understanding: Extracting Meaning and Context from Textual Content* - Docdigitizer. [online] Available at: https://www.docdigitizer.com/blog/natural-language-processing-nlp-for-document-understanding

Dogru, A.K. and Keskin, B.B. (2020). *AI in operations management: applications, challenges and opportunities*. Journal of Data, Information and Management, [online] 2(2), pp.67–74. doi: https://doi.org/10.1007/s42488-020-00023-1.

Dr. Ankush Agrawal and Mitra, A. (2023). *SAP S/4HANA Supply Chain Planning and Manufacturing*. BPB Publications.

Emerald Publishing. (2024). *The evolving role of generative AI in digital marketing and branding*. Journal of Consumer Marketing. https://doi.org/10.1108/jcm-06-2024-6922

Esri. (2025). Video: *Inside Zurich's Digital Twin for Infrastructure Management*. [online] Available at: https://www.esri.com/about/newsroom/blog/video-geospatial-digital-twin-powers-infrastructure-management-in-zurich

ETH AI Center. (2025). *AI in Retail & Smart Cities & Mobility*. [online] Available at: https://ai.ethz.ch/research/core-areas/ai-retail-smart-cities-mobility.html

European Commission (2023). *A European approach to Artificial intelligence* | Shaping Europe's digital future. [online] digital-strategy.ec.europa.eu. Available at: https://digital-strategy.ec.europa.eu/en/policies/european-approach-artificial-intelligence.

European Commission (2024). *Smart cities*. [online] commission.europa.eu. Available at: https://commission.europa.eu/eu-regional-and-urban-development/topics/cities-and-urban-development/city-initiatives/smart-cities_en.

ewz. (2024). 2,*000-watt society* | Our commitment | ewz. [online] Available at: https://www.ewz.ch/en/about-ewz/portrait/commitment/2000-watt-society.html

Fabbrocino, R. (2023). *Oslo becoming the world's first capital with a zero-emissions public transport system*. [online] Lampoon Magazine. Available at: https://lampoonmagazine.com/article/2023/01/13/oslo-becoming-the-worlds-first-capital-with-a-zero-emissions-public-transport-system.

Feldstein, S. (2021). *The rise of digital repression: How technology is reshaping power, politics, and resistance.* Oxford University Press. https://global.oup.com/academic/product/the-rise-of-digital-repression-9780190057497?cc=it&lang=en&

Feng-hsiung Hsu. (2022). *Behind Deep Blue.* [online] Available at: https://books.google.it/books?hl=it&lr=&id=7aBMEAAAQBAJ&oi=fnd&pg=PR7&dq=IBM

Ferrera, M. (2025). *City Brain di Alibaba, come l'IA rivoluziona un brand e una città*. [online] Digital School. Available at: https://www.digitalschool.com/blog/city-brain-alibaba-come-intelligenza-artificiale-rivoluziona-un-brand-e-una-citta/

Feuerriegel, S., Hartmann, J., Janiesch, C. and Zschech, P. (2023). *Generative AI*. Business & Information Systems Engineering. doi: https://doi.org/10.1007/s12599-023-00834-7.

Garcia, E. (2022). *AI-Driven Noise Pollution Monitoring and Mitigation in Smart Cities*. [online] Philpapers.org. Available at: https://philpapers.org/rec/GARANP-7

Government-fleet.com (2024). How Two Companies Are Using AI to Transform Fleet Management. [online]. Available at: https://www.government-fleet.com/10226592/how-two-companies-are-using-ai-to-transform-fleet-management

Haleem, A., Javaid, M., Singh, R.P., Rab, S. and Suman, R. (2021). *Hyperautomation for the enhancement of automation in industries. Sensors International*, [online]. doi: https://doi.org/10.1016/j.sintl.2021.100124.

Haque, A.B., Islam, A.K.M.N. and Mikalef, P. (2023). *Explainable Artificial Intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research.* Technological Forecasting and Social Change. doi: https://doi.org/10.1016/j.techfore.2022.122120.

Harvard Business Review, 2023, A*I and the Future of Work: Adapting Business Strategies for Automation*, HBR Journal. https://hbr.org

Herath, H.M.K.K.M.B. and Mittal, M. (2022). *Adoption of artificial intelligence in smart cities: A comprehensive review. International Journal of Information Management Data Insights*, [online]. Available at: https://www.sciencedirect.com/science/article/pii/S2667096822000192.

Holaday, C. (2024). '*Life-saving' AI cuts travel time by 32 mins for vehicles racing to crash scenes – and it's already 'widely used'* [online] The US Sun. Available at: https://www.the-sun.com/motors/13134325/traffic-ai-lyt-laramie-bowron/.

Holzinger, A., Langs, G., Denk, H., Zatloukal, K. and Müller, H. (2019). *Causability and explainability of artificial intelligence in medicine*. WIREs Data Mining and Knowledge Discovery, [online]. doi: https://doi.org/10.1002/widm.1312.

Hsu, Y.-C., Huang, T.-H. 'Kenneth', Verma, H., Mauri, A., Nourbakhsh, I. and Bozzon, A. (2022). *Empowering local communities using Artificial Intelligence*. Patterns. https://doi.org/10.1016/j.patter.2022.100449

https://books.google.it/books?hl=it&lr=&id=nHp8DwAAQBAJ&oi=fnd&pg=PR7&dq=Batty

Huber, N. (2025). *AI business technology takes on shoplifters and admin drag*. [online] @FinancialTimes. Available at: https://www.ft.com/content/b7674c60-8234-432a-b70b-b5b48a98cf32.

IEA (2017). *Digitalization and Energy – Analysis*. [online] IEA. Available at: https://www.iea.org/reports/digitalisation-and-energy.

IMD. (2025). *IMD_Smart_City_2025_Report.pdf*. [online] Available at: https://imd.widen.net/s/psdrsvpbk7/imd_smart_city_2025_report.

Inel, O., Draws, T. and Aroyo, L. (2023). *Collect, Measure, Repeat: Reliability Factors for Responsible AI Data Collection*. Proceedings of the AAAI Conference on Human Computation and Crowdsourcing, Available at: https://doi.org/10.1609/hcomp.v11i1.27547

Infosys Limited (2025). *AI powered MaaS*. [online] Infosys.com. Available at: https://blogs.infosys.com/digital-experience/emerging-technologies/ai-powered-maas.html

INRIX (2025). *Global Traffic Scorecard*. [online] Inrix. Available at: https://inrix.com/scorecard/#form-download-the-full-report.

J.P. Morgan (2023). AI Boosting Payments Efficiency & Cutting Fraud | J.P. Morgan. [online] www.jpmorgan.com. Available at: https://www.jpmorgan.com/insights/payments/payments-optimization/ai-payments-efficiency-fraud-reduction

Jeyadev Needhi (2024). *How AI Transformed Financial Fraud Detection: A Case Study of JP Morgan Chase*. [online] Medium. Available at:

https://medium.com/@jeyadev_needhi/how-ai-transformed-financial-fraud-detection-a-case-study-of-jp-morgan-chase-f92bbb0707bb

Journal, A.B.A. (2017). *JPMorgan Chase uses tech to save 360,000 hours of annual work by lawyers and loan officers*. [online] ABA Journal. Available at: https://www.abajournal.com/news/article/jpmorgan_chase_uses_tech_to_save_360000_hours_of_annual_work_by_lawyers_and.

Kaganer, E., Gregory, R. and Sarker, S. (2023). *A Process for Managing Digital Transformation: An Organisational Inertia Perspective*. Journal of the Association for Information Systems, [online]. https://doi.org/10.17705/1jais.00819

Kanton Zürich. (2025). *Verkehrsdaten*. [online] Available at: https://www.zh.ch/de/mobilitaet/gesamtverkehrsplanung/verkehrsgrundlagen/verkehrsdaten.html.

Khandani, A.E., Kim, A.J. and Lo, A.W. (2010). *Consumer credit-risk models via machine-learning algorithms*. Journal of Banking & Finance. doi: https://doi.org/10.1016/j.jbankfin.2010.06.001.

Kumar, A. and Bahl, R., 2022. *A study of barriers and benefits of Artificial Intelligence adoption in small and medium enterprise*. [pdf] ResearchGate. Available at: https://www.researchgate.net/publication/360912025_A_STUDY_OF_BARRIERS_AND_BENEFITS_OF_ARTIFICIAL_INTELLIGENCE_ADOPTION_IN_SMALL_AND_MEDIUM_ENTERPRISE

Kumar, A., Asad, A., Brooks, B., Ali, V.R., Wilson, K.H., Kenney, C., Edelstein, S., Finch, A., Maxwell, A., Zuckerbraun, J. and Ghani, R. (2018). *Using Machine Learning to Assess the Risk of and Prevent Water Main Breaks*. [online] arXiv.org. Available at: https://arxiv.org/abs/1805.03597

Lasaite, L. (2024). *Ethical Considerations and Challenges of AI Adoption in Project Management*, pp.204–218. https://doi.org/10.1007/978-3-031-56310-2_16

Lehtola, V.V., Koeva, M., Elberink, S.O., Raposo, P., Virtanen, J.-P., Vahdatikhaki, F. and Borsci, S. (2022). *Digital twin of a city: Review of technology serving city* *needs*. International Journal of Applied Earth Observation and Geoinformation, [online]. doi:https://doi.org/10.1016/j.jag.2022.102915.

Leslie, D. (2020). *Explaining Decisions Made with AI*. SSRN Electronic Journal. doi: https://doi.org/10.2139/ssrn.4033308.

Shinde, P.P. and Shah, S. (2018). *A Review of Machine Learning and Deep Learning Applications*. [online] IEEE Xplore. doi: https://doi.org/10.1109/ICCUBEA.2018.8697857.

Lisandro Arturo Jimenez-Roa, Simão, T.D., Zaharah Bukhsh, Tiedo Tinga, Hajo Molegraaf, Jansen, N. and Stoelinga, M. (2024). *Maintenance Strategies for Sewer Pipes with Multi-State Degradation and Deep Reinforcement Learning*. PHM Society European Conference. doi: https://doi.org/10.36001/phme.2024.v8i1.4091.

Lv, Z. (2023). *Digital Twins in Industry 5.0*. Research. doi: https://doi.org/10.34133/research.0071.

Machine Intelligence and Data Analytics for Sustainable Future Smart Cities. (2021). Springer eBooks. doi: https://doi.org/10.1007/978-3-030-72065-0.

Mandvikar, S. (2023). *Process Automation 2.0 with Generative AI Framework*. ResearchGate. https://www.researchgate.net/publication/375000709

Mani, G., Viswanadhapalli, J.K. and Sriramalakshmi, P. (2021). *AI powered IoT based Real-Time Air Pollution Monitoring and Forecasting*. Journal of Physics: Conference Series. https://doi.org/10.1088/1742-6596/2115/1/012016

Manisha Salecha (2016). *Artificial Narrow Intelligence vs Artificial General Intelligence | AIM Media House*. [online] Analytics India Magazine. Available at: https://analyticsindiamag.com/ai-features/artificial-narrow-intelligence-vs-artificial-general-intelligence

Mattar, A. (2024). *Harnessing IoT, Big Data, and AI to Drive Mobility as a Service (MaaS) in Smart Cities*. [online] Linkedin.com. Available at: https://www.linkedin.com/pulse/harnessing-iot-big-data-ai-drive-mobility-service-maas-alaa-mattar-ancnf/.

Mayors of Europe. (2024). *Transforming Urban Living - Insights from the IMD Smart City Index 2024 on Europe's Leading and Lagging Cities* | Mayors of Europe. [online] Available at: https://mayorsofeurope.eu/science-and-the-city/transforming-urban-living-insights-from-the-imd-smart-city-index-2024-on-europes-leading-and-lagging-cities/.

Mazhar Rathore, M., Shah, S.A., Shukla, D., Bentafat, E. and Bakiras, S. (2021). *The Role of AI, Machine Learning, and Big Data in Digital Twinning: A Systematic Literature Review, Challenges, and Opportunities*. IEEE. doi: https://doi.org/10.1109/access.2021.3060863.

McKinsey & Company, 2023, *The state of AI in 2023: Generative AI's breakout year*, McKinsey Report. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year

Medhat, W., Hassan, A. and Korashy, H. (2014). *Sentiment Analysis Algorithms and applications: a Survey*. Ain Shams Engineering Journal, [online]. Doi: https://doi.org/10.1016/j.asej.2014.04.011.

Mendelsohn, S. (2024). *AI will accelerate sustainability, but is no silver bullet*. [online] doi: https://www.weforum.org/stories/2024/09/ai-accelerator-sustainability-silver-bullet-sdim/

Michael Batty. (2018). *Inventing Future Cities*. [online] Available at:

Mittelstadt, B.D., Allo, P., Taddeo, M., Wachter, S. and Floridi, L. (2016). *The Ethics of algorithms: Mapping the Debate*. Big Data & Society. doi: https://doi.org/10.1177/2053951716679679.

Morgan Stanley (2023) *2023 ESG Report*. Available at: https://www.morganstanley.com/content/dam/msdotcom/en/assets/pdfs/Morgan_Stanley_2023_ESG_Report.pdf

Muhammad Waqar, Bhatti, I., Khan, A.H. and Lucas, M. (2024). *AI-Powered Automation: Revolutionising Industrial Processes and Enhancing Operational Efficiency*. [online] Available at: https://www.researchgate.net/publication/386076266_AI-Powered_Automation_Revolutionising_Industrial_Processes_and_Enhancing_Operational_Efficiency.

Nayak, R., Nayyar, A., & Puri, V. (2020). *Smart Automated Systems Using Artificial Intelligence: A Review.* arXiv preprint arXiv:2007.13257. Retrieved from https://arxiv.org/pdf/2007.13257

Nuti, G., Mirghaemi, M., Treleaven, P. and Yingsaeree, C. (2011). *Algorithmic Trading*. Computer. doi: https://doi.org/10.1109/mc.2011.31.

OECD. (2024). *The OECD Programme on Smart Cities and Inclusive Growth*. [online] Available at: https://www.oecd.org/en/about/programmes/the-oecd-programme-on-smart-cities-and-inclusive-growth0.html.

Office, F.S. (2024). *Road vehicles - Stock, level of motorisation*. [online] www.bfs.admin.ch. Available at: https://www.bfs.admin.ch/bfs/en/home/statistics/mobility-transport/transport-infrastructure-vehicles/vehicles/road-vehicles-stock-level-motorisation.html.

Oyadeyi, O.A. and Oyadeyi, O.O. (2025). *Towards Inclusive and Sustainable Strategies in Smart cities: a Comparative Analysis of Zurich, Oslo, and Copenhagen*. Research in Globalization, [online]. doi:https://doi.org/10.1016/j.resglo.2025.100271.

Pandy, G. (2024). *Generative AI: Transforming the Landscape of Creativity and Automation*. ResearchGate. https://www.researchgate.net/publication/388556366

Petrenko, V. (2024). *AI in Transportation: How AI Technology is Revolutionizing Traffic Management*. [online] Litslink. Available at: https://litslink.com/blog/ai-and-transportation.

Puomio, S. (2021). *What is an urban digital twin?* - Forum Virium Helsinki. [online] Forum Virium Helsinki. Available at: https://forumvirium.fi/en/what-is-an-urban-digital-twin/

PwC, 2023, *AI's $15.7 Trillion Impact on the Global Economy*, PwC AI Report. https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf

Quang Thao, L., Duc Cuong, D., Thi Tuong Anh, T. and Duc Luong, T. (2023). *Profiling of Urban Noise Using Artificial Intelligence*. Computer Systems Science and Engineering. doi: https://doi.org/10.32604/csse.2023.031010.

Rajabi, E., Nowaczyk, S., Sepideh Pashami, Bergquist, M., Geethu Susan Ebby and Summrina Wajid (2023). *A Knowledge-Based AI Framework for Mobility as a Service*. Sustainability, [online]. doi: https://doi.org/10.3390/su15032717.

Rani, V., Nabi, S.T., Kumar, M., Mittal, A. and Kumar, K. (2023). *Self-supervised Learning: A Succinct Review*. Archives of Computational Methods in Engineering. doi: https://doi.org/10.1007/s11831-023-09884-2.

Reddy, P., Chaitanya, V. and Gupta, A., 2021. *Optimising Public Transport Services using AI to Reduce Congestion in Metropolitan Areas*. Available at: https://research.tensorgate.org/index.php/IJIAC/article/download/34/39

Sanchez, T.W., Brenman, M. and Ye, X. (2024). *The Ethical Concerns of Artificial Intelligence in Urban Planning*. Journal of the American Planning Association. doi: https://doi.org/10.1080/01944363.2024.2355305.

Schrotter, G. and Hürzeler, C. (2020). *The Digital Twin of the City of Zurich for Urban Planning.* PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science, doi: https://doi.org/10.1007/s41064-020-00092-2.

Selvarajan, G.P. (2021) *'Leveraging AI-Enhanced Analytics for Industry-Specific Optimisation: A Strategic Approach to Transforming Data-Driven Decision-Making'*, International Journal of Enhanced Research in Management & Computer Applications. Available at: https://www.researchgate.net/publication/385627137_Leveraging_AI-Enhanced_Analytics_for_Industry-Specific_Optimisation_A_Strategic_Approach_to_Transforming_Data-Driven_Decision-Making

Sharma, A.K., Sharma, D.M., Purohit, N., Rout, S.K. and Sharma, S.A. (2022). *Analytics Techniques: Descriptive Analytics, Predictive Analytics, and Prescriptive Analytics*. Decision Intelligence Analytics and the Implementation of Strategic Business Management, pp.1–14. doi: https://doi.org/10.1007/978-3-030-82763-2_1.

Shinde, A., Pawar, D. and Sonawane, K. (2021). *Automation in pharmaceutical sector by implementation of Artificial Intelligence platform: a way forward*. International Journal of Basic & Clinical Pharmacology. https://doi.org/10.18203/2319-2003.ijbcp20212387

Shortliffe, E.H. (1977). *Mycin: A Knowledge-Based Computer Program Applied to Infectious Diseases. Proceedings of the Annual Symposium on Computer Application in Medical Care*. Available at: https://pmc.ncbi.nlm.nih.gov/articles/PMC2464549/

Sill Lighting. (2024). *Intelligent city lighting, Zurich* | Sill Lighting. [online] Available at: https://sill-lighting.com/en/projects/intelligent-city-lighting-zuerich/.

Simonofski, A., Hertoghe, E., Steegmans, M., Snoeck, M. and Wautelet, Y. (2021). *Engaging citizens in the smart city through participation platforms: A framework for public servants and developers*. Computers in Human Behavio. doi: https://doi.org/10.1016/j.chb.2021.106901.

Smith, S., Barlow, G., Xie, X.-F. and Rubinstein, Z. (2013). *SURTRAC: Scalable Urban Traffic Control*. [online] Available at: https://www.ri.cmu.edu/pub_files/2013/1/13-0315.pdf.

Snigdha, E. Z., Hossain, M. R., & Mahabub, S. (2023). *AI-Powered Healthcare Tracker Development: Advancing Real-Time Patient Monitoring and Predictive Analytics Through Data-Driven Intelligence*. Journal of Computer Science and Technology Studie. https://doi.org/10.32996/jcsts.2023.5.4.24

Sohel Rana, (2025). *AI-DRIVEN FAULT DETECTION AND PREDICTIVE MAINTENANCE IN ELECTRICAL POWER SYSTEMS: A SYSTEMATIC REVIEW OF DATA-DRIVEN APPROACHES, DIGITAL TWINS, AND SELF-HEALING GRIDS*. American Journal of Advanced Technology and Engineering Solutions [online] 1(01). doi: https://doi.org/10.63125/x6ypjm21.

Sowri, M., Banana, K., Com, M. and Phil, M. (2024). *A STUDY ON NARROW ARTIFICIAL INTELLIGENCE-AN OVERVIEW*. International Journal of Engineering Science and Advanced Technolo 24. Available at: https://www.ijesat.com/ijesat/files/V24I0428_1714383466.pdf.

Stadt-zuerich.ch. (2024). *Smart City*. [online] Available at: https://www.stadt-zuerich.ch/de/politik-und-verwaltung/politik-und-recht/strategie-politikfelder/smart-city.html

Storey, V.C., Yue, W.T., Zhao, J.L. and Lukyanenko, R. (2025). *Generative Artificial Intelligence: Evolving Technology, Growing Societal Impact, and Opportunities for Information Systems Research*. Information Systems Frontiers. doi: https://doi.org/10.1007/s10796-025-10581-7.

Stryker, C., Kavlakoglu, E., (2024). *What is artificial intelligence (AI)?* Ibm.com. Available at: https://www.ibm.com/think/topics/artificial-intelligence

Tangi, L., Colin van Noordt and Rodriguez, P. (2023). *The challenges of AI implementation in the public sector*. An in-depth case studies analysis. doi: https://doi.org/10.1145/3598469.3598516.

Taylor, A. (2025). *How Walmart and Amazon Are Redefining Retail Efficiency with AI-Powered Logistics*. Cleverence.com. Available at: https://www.cleverence.com/articles/business-blogs/how-walmart-and-amazon-are-redefining-retail-efficiency-with-ai-powered-logistics/.

Team DigitalDefynd (2024). 5 ways JP Morgan is using AI - Case Study [2024]. [online] DigitalDefynd. Available at: https://digitaldefynd.com/IQ/jp-morgan-using-ai-case-study/

Terra, L. (2024). Smart city -*La città 'intelligente' del futuro*. [online] Available at: https://www.bps-suisse.ch/pdf/pubb_news_esg_n_deg__10_smart_city_1.pdf

Tomor, Z., Przeybilovicz, E. and Leleux, C. (2021). *Smart governance in institutional context: An in-depth analysis of Glasgow, Utrecht, and Curitiba*. Cities. doi: https://doi.org/10.1016/j.cities.2021.103195.

Toosi, A., Bottino, A.G., Saboury, B., Siegel, E. and Rahmim, A. (2021). *A Brief History of AI: How to Prevent Another Winter* (A Critical Review). PET Clinics, 16(4), pp.449–469. https://pubmed.ncbi.nlm.nih.gov/34537126/

UN-Habitat, (2022), *Annual report 2022UNITED NATIONS HUMAN SETTLEMENT PROGRAMME*. Available at: https://unhabitat.org/sites/default/files/2023/06/unhabitat_annualreport_2022.pdf

UNDP. (2024). *Bringing Communities Together Through AI-Driven Urban Planning*. [online] Available at: https://www.undp.org/acceleratorlabs/blog/bringing-communities-together-through-ai-driven-urban-planning.

UNESCO (2023). *Recommendation on the Ethics of Artificial Intelligence | UNESCO*. [online] www.unesco.org. Available at: https://www.unesco.org/en/articles/recommendation-ethics-artificial-intelligence

Vagelis Plevris and Papazafeiropoulos, G. (2024). *AI in Structural Health Monitoring for Infrastructure Maintenance and Safety*. Infrastructures, [online]. doi: https://doi.org/10.3390/infrastructures9120225.

VBZ Züri-Linie (2024). *VBZ DigitalTwin*. [online] YouTube. Available at: https://www.youtube.com/watch?v=Gyf3Kz13T7w

Walker. A. (2025). *Zurich Installed 4,500 Street Sensors to Count Every Car in the City*. [online] Available at: https://gizmodo.com/zurich-installed-4-500-street-sensors-to-count-every-ca-1647223392

Walters, A. (2019). *National Digital Twin Programme*. [online] www.cdbb.cam.ac.uk. Available at: https://www.cdbb.cam.ac.uk/what-we-did/national-digital-twin-programme.

Wang, Y. (2023). *Generative AI in Operational Risk Management: Harnessing the Future of Finance*. [online] Social Science Research Network. https://doi.org/10.2139/ssrn.4452504

Weinzierl, S., Zilker, S., Dunzer, S. and Matzner, M. (2024). *Machine learning in business process management: A systematic literature review*. [online] arXiv.org. Available at: https://arxiv.org/abs/2405.16396.

Wolniak, R. and Stecuła, K. (2024). *Artificial Intelligence in Smart Cities: Applications, Barriers, and Future Directions: A Review*. Smart Cities, [online]. doi: https://doi.org/10.3390/smartcities7030057.

World Economic Forum (January 2025). *Blueprint to Action: China's Path to AI-Powered Industry Transformation*. Available at: https://reports.weforum.org/docs/WEF_Blueprint_to_Action_Chinas_Path_to_AI-Powered_Industry_Transformation_2025.pdf

World Economic Forum. Available at: https://www.weforum.org/stories/2024/09/ai-accelerator-sustainability-silver-bullet-sdim/.

Zha, J. (2020). *Artificial Intelligence in Agriculture*. Journal of Physics: Conference Series, 1693. doi: https://doi.org/10.1088/1742-6596/1693/1/012058.

ZHAW Zurich University of Applied Sciences. (2015). *Smart Cities* | ZHAW Zurich University of Applied Sciences. [online] Available at: https://www.zhaw.ch/en/research/project/70962

Zitha, P. and Thango, B.A. (2023). *On the Study of Induction Motor Fault Identification using Support Vector Machine Algorithms*. 2023 31st Southern African Universities Power Engineering Conference (SAUPEC), [online]. doi: https://doi.org/10.1109/saupec57889.2023.10057836.

Zonta, T., da Costa, C.A., da Rosa Righi, R., de Lima, M.J., da Trindade, E.S. and Li, G.P. (2020). *Predictive maintenance in the Industry 4.0: A systematic literature review*. Computers & Industrial Engineering. doi: https://www.sciencedirect.com/science/article/abs/pii/S0360835220305787

Zubair, A. (n.d.). *Domain Awareness System*. [online] Available at: https://static1.squarespace.com/static/5c1bfc7eee175995a4ceb638/t/5d8cea6ffe6f0353873d14c5/1569516145398/Domain+Awareness.pdf

LUISS

Department
of Management

Chair of Artificial Intelligence & Digital Marketing

From Business Operations to Smart Cities: How Artificial Intelligence can be Levered for Urban Optimisation and Monitoring

Summary

Prof. Maximo Ibarra
SUPERVISOR

Prof. Luigi Laura
CO-SUPERVISOR

Matteo Ferracioli
CANDIDATE

Academic Year 2024/2025

SUMMARY

An Introduction to AI

The introductory section of the thesis offers a thorough exploration of the concept of Artificial Intelligence (AI), beginning with a review of its multidisciplinary foundations across computer science, mathematics, cognitive science, and systems theory. The discussion opens with a conceptual definition of AI as the ability of a system to perform tasks that typically require human intelligence, such as reasoning, learning, perception, and decision-making. From there, the section retraces the historical trajectory of AI, from the early symbolic and rule-based approaches of the 1950s and 1960s, exemplified by the development of expert systems and logical inference engines, to the paradigm shift introduced by machine learning and, subsequently, deep learning in the 2000s.

Particular attention is given to the technological enablers that made this evolution possible, such as the exponential growth of computational power, the availability of large-scale datasets, and advances in neural network architectures. These developments have allowed AI systems to progress from deterministic logic to probabilistic, adaptive, and autonomous systems capable of pattern recognition, predictive modelling, and real-time optimisation.

This foundational chapter also serves a methodological function, establishing the rationale for examining AI not merely as a technological innovation, but as a systemic force capable of reshaping both business processes and urban environments. The increasing integration of AI technologies into organisational workflows, ranging from logistics and process automation to strategic planning, has catalysed a new digital paradigm that now extends into public governance and urban management.

In this context, the chapter introduces the dual focus of the research: firstly, to understand how AI enhances operational efficiency and decision-making within business contexts, and secondly, to explore how those same technologies can be adapted and scaled to address the complexity of urban systems. The chapter frames the relevance of AI within broader digital transformation trends and articulates the socio-economic imperatives, such as sustainability, resilience, and inclusivity, that justify the need for a critical, cross-sectoral examination of AI's role in shaping the cities of the future.

Chapter 1 – AI for Business Operations: A Foundation for Urban Innovation

This chapter examines the transformative role of Artificial Intelligence (AI) in business operations and lays the conceptual groundwork for understanding how corporate-level digital innovation serves as a precursor to urban-scale technological integration. It argues that the implementation of AI within organisational contexts not only increases efficiency and adaptability but also generates scalable models that are directly translatable to public infrastructure and smart governance frameworks.

The chapter begins by analysing how AI contributes to the automation of operational processes, the optimisation of resource allocation, and the enhancement of real-time decision-making. It explains how the shift from rule-based systems to data-driven models allows organisations to move from reactive to predictive and even prescriptive modes of operation. These capabilities are examined through the lens of data analytics, which enables the extraction of actionable insights from large and heterogeneous datasets, often in dynamic or high-stakes environments.

Subsequently, the chapter explores the technological building blocks that underpin these applications. Particular focus is placed on machine learning algorithms, which support adaptive behaviour through iterative training and performance feedback; natural language processing (NLP), which facilitates AI-human interaction and knowledge extraction from unstructured data; and explainable AI (XAI), which addresses the critical need for transparency and accountability in decision-support systems. Each of these components is analysed not only in terms of their technical mechanisms but also in relation to their strategic and managerial implications, especially in contexts requiring reliability, compliance, and user trust.

A key analytical section is dedicated to emerging technologies such as generative AI and digital twins. Generative AI models, including large language models and generative adversarial networks, are discussed in their capacity to autonomously produce content, simulate scenarios, and support innovation through synthetic data generation. Digital twins, defined as dynamic, real-time digital replicas of physical assets or systems, are analysed as tools that offer continuous monitoring, scenario testing, and predictive maintenance capabilities. These systems are positioned as bridges between physical operations and digital intelligence, offering a preview of how AI can support urban planning, energy management, and mobility systems in a smart city context.

In addition to technological enablers, the chapter critically assesses the organisational conditions necessary for effective AI integration. These include the need for data governance frameworks, the development of digital capabilities within teams, and the alignment of AI adoption with business strategy. It also highlights several risks and challenges, such as algorithmic bias, system opacity, cybersecurity vulnerabilities, and resistance to change, especially in highly regulated or structurally conservative industries.

Ultimately, the chapter demonstrates that AI in business is not only a vector of internal optimisation but also a conceptual and operational laboratory for public-sector innovation. By drawing parallels between enterprise process transformation and the structural needs of urban systems, the chapter argues that AI's success in business provides both a technological foundation and a methodological blueprint for its deployment in smart cities. This interconnection sets the stage for the subsequent chapters, where similar technologies and frameworks are explored in the context of urban infrastructure, mobility, and public governance.

Chapter 2 – AI in Smart Cities: Predictive Maintenance and Transport Optimisation

Chapter 2 explores the application of Artificial Intelligence (AI) within the context of smart cities, focusing on how intelligent technologies are transforming the management of infrastructure, mobility, environmental quality, and public safety. It begins by framing the smart city as a data-driven urban ecosystem, in which AI functions not only as a technical instrument but also as a strategic enabler of proactive governance, sustainability, and inclusive service delivery. Rather than being confined to isolated technological interventions, AI is conceptualised as a systemic force capable of reshaping urban dynamics and fostering preventive policy actions.

The chapter highlights how AI-based predictive maintenance systems, supported by Internet of Things (IoT) sensors and digital twins, are replacing traditional time-based maintenance models with condition-based approaches. These digital twins, dynamic real-time virtual models of physical assets such as roads, bridges, and utilities, allow cities to simulate operational conditions, monitor infrastructure status, and anticipate failures before they occur. This transition enables more efficient resource allocation, reduces service disruptions, and enhances public safety, as demonstrated by early implementations in cities like Zurich. At the same time, these technologies contribute to aligning urban infrastructure management with broader goals of sustainability and resilience.

The analysis then shifts to the application of AI in urban mobility, illustrating how machine learning algorithms and adaptive systems support real-time traffic monitoring, congestion mitigation, and public transport scheduling. By integrating multimodal data and user behaviour, these technologies facilitate intelligent route planning and dynamic adjustments that improve both efficiency and user experience. Notably, the theoretical frameworks are applied in platforms such as Mobility-as-a-Service (MaaS), integrated ecosystems that combine various modes of transport within a single digital interface. Through AI, these systems are able to learn from and adapt to changing patterns of demand, enabling cities to offer seamless, sustainable, and personalised mobility solutions that reduce reliance on private vehicles and contribute to the achievement of environmental targets.

The chapter also examines the role of AI in environmental and safety monitoring, with particular attention to how sensor networks and predictive analytics are employed to monitor air quality, detect noise pollution, and assess urban risk factors. It acknowledges that while these systems have the potential to enhance real-time awareness and responsiveness, they also raise ethical concerns regarding surveillance, privacy, and algorithmic accountability. Such concerns should not be viewed as obstacles to technological development, but rather as critical dimensions to be addressed through transparent governance and regulatory oversight.

It is essential, in analysing these contexts, to also consider the structural and socio-political barriers to the widespread adoption of AI in urban governance. These include limitations in funding, technological integration, institutional capacity, and digital literacy, as well as issues of social equity and citizen participation, often linked to trust in policy outcomes and in the handling of citizens' personal data. Particular emphasis is placed on the risks of excluding vulnerable populations from AI-based services and the importance of designing systems that are not only technically robust, but also socially inclusive and ethically aligned.

Chapter 2 thus demonstrates that AI, when strategically integrated into urban systems, has the potential to significantly enhance cities' operational intelligence. It builds directly upon the technologies discussed in Chapter 1 within the business context and sets the stage for the empirical validation provided in Chapter 3, in which Zurich is analysed as a key example of intelligent urban transformation.

Chapter 3 – Case Studies: AI Implementation in Leading Smart Cities

Chapter 3 builds on the theoretical and technological insights developed in the previous sections, applying them to a concrete empirical context: the city of Zurich. Positioned at the top of the IMD Smart City Index 2025, Zurich serves as a benchmark for the integration of Artificial Intelligence (AI) into complex urban systems. The chapter adopts Zurich as a paradigmatic case to examine how AI can be effectively implemented at the municipal level when supported by long-term strategic planning, institutional coordination, and a governance model grounded in public accountability and ethical principles.

The analysis begins by positioning Zurich within the global landscape of leading smart cities, followed in the rankings by cities such as Oslo, Geneva, Dubai, and Abu Dhabi. Zurich was selected for an in-depth analysis due to its systemic and multidimensional adoption of AI technologies. The city's strategic vision is closely aligned with its longstanding commitment to environmental sustainability, operational efficiency, and citizen-centred service design, as well as with objectives materialised through initiatives such as the "2000-Watt Society" programme and climate neutrality targets, which are actively supported by AI-enhanced infrastructures and real-time data systems.

The chapter details Zurich's implementation of intelligent technologies in critical urban domains. AI is applied to adaptive street lighting, traffic flow optimisation, and predictive maintenance of public assets. In particular, the city leverages digital twins, virtual models of physical infrastructure based on real-time data, developed in collaboration with ETH

Zurich and ZHAW, to simulate traffic patterns, monitor structural conditions, and dynamically plan resource allocation. These technologies operate within an integrated feedback loop, in which IoT-generated data are continuously analysed by machine learning systems to inform real-time policy adjustments and operational decisions. Rather than isolated innovations, these tools form part of an interconnected digital architecture that enables the city to monitor, predict, and optimise performance across multiple sectors.

Zurich's approach has yielded measurable results, securing its first-place ranking in the global index for several consecutive years. Data from the IMD index and other performance indicators show improvements in energy efficiency, emissions reduction, service reliability, and digital inclusion. At the same time, the chapter provides a critical perspective, acknowledging that not all objectives have been fully achieved. Traffic congestion remains a persistent challenge according to residents, and participation in digital governance platforms remains uneven. These observations underscore the importance of addressing socio-digital inequalities and ensuring that AI-based solutions are accessible, interpretable, and responsive to the diverse needs of citizens.

Drawing from the example of Zurich, the chapter synthesises the key conditions for effective AI integration into urban governance: a coherent and future-oriented strategic framework, robust public–private–academic partnerships, continuous investment in technological infrastructure, and a commitment to algorithmic transparency and citizen trust. While Zurich's model is deeply context-specific, its core principles, systemic thinking, ethical design, cross-sector coordination, and long-term strategic investment, are presented as transferable reference points for other cities seeking to responsibly scale AI within their urban ecosystems.

Chapter 4 - A personal analysis of the inhabitants' considerations

Chapter 4 introduces the empirical dimension of the thesis through a structured analysis of a survey designed to capture citizens' perceptions, awareness, and attitudes regarding the adoption of Artificial Intelligence (AI) in urban contexts. Conducted in April 2025 and distributed online via social platforms and professional networks, the survey involved 151 respondents, primarily aged between 21 and 35, residing in or connected to three key urban centres: Zurich, London, and Rome. These cities were selected for their relevance to the case study, their prominence in international smart city rankings, and their varying levels of digital infrastructure development. The survey pursued a dual purpose: on the one hand, it provided empirical validation of the theoretical assumptions and case-based analyses developed in the preceding chapters; on the other, it offered a deeper understanding of the social factors influencing public acceptance of AI in urban governance, with particular attention to issues of trust, data privacy, service quality, and perceived benefits.

The collected data reveal a predominantly positive orientation toward AI, with 93% of respondents expressing support for its integration in smart cities and articulating clear expectations regarding its potential to enhance public services. Among the sectors considered most suitable for AI application, urban mobility and traffic management ranked highest, cited by 90% of participants, followed by environmental and energy services (71%) and waste management (68%). These findings reflect not only public interest in functional efficiency but also an increasing awareness of sustainability as a technological imperative. Notably, these preferences were expressed independently of any prior information regarding the current level of AI implementation in the cities considered, suggesting a perceptual alignment between citizens' intuitive expectations and the areas where AI is already actively deployed.

The survey further assessed the extent to which AI is integrated into respondents' daily routines. Despite more than one third of participants reporting a limited understanding of how AI works, 89% stated they use AI-based applications on a daily or near-daily basis. These include navigation tools such as Google Maps and Waze, mobility platforms such as Uber and Free Now, and micro-mobility solutions such as Lime. 81% of users considered these tools not only useful, but essential for the organisation of daily life. This result underscores the often-invisible ubiquity of AI in the urban experience and reinforces the notion that low awareness does not preclude high levels of use and perceived utility.

A central focus of the survey was the ethical dimension of data governance. While only 4% of respondents categorically opposed data sharing, 50% supported it under the condition of strict anonymity, and 36% expressed a preference for data usage restricted solely to objectives of public interest. Just 10% indicated full and unconditional consent. These results underscore the importance of transparency, institutional credibility, and ethical safeguards as prerequisites for the legitimacy of AI-based governance systems. Closely related to this is the demand for clarity in automated decision-making processes, with 97% of respondents stating that it is important or essential to know when a decision affecting their lives has been made by an AI system rather than by a human authority. This overwhelming consensus points to a strong social demand for algorithmic accountability and the development of interfaces capable of clearly communicating the origin and logic of automated actions.

Lastly, the survey explored whether the presence of smart city features might influence residential preferences. 72% of participants affirmed that a city's technological advancement would be a determining factor in choosing where to live, while an additional 6% noted it would still play a significant role. Only 22% stated that it would have no influence on their decision. This result confirms that the intelligence of a city is no longer a purely institutional or technical issue but a tangible element of urban desirability and personal quality of life.

In summary, Chapter 4 confirms that AI is not only functionally integrated into urban life but is also widely recognised by citizens as a legitimate and desirable driver of urban transformation. However, public support is not unconditional. It depends on trust, ethical governance, and mechanisms that ensure transparency, participation, and inclusion. The results suggest that societal readiness for AI adoption is high, but so too are expectations about how it should be managed. These insights offer a crucial complement to the technical and institutional analyses of the previous chapters, adding a human-centred perspective that is essential for any comprehensive understanding of intelligent urban innovation.

Conclusion

This thesis has examined the role of Artificial Intelligence (AI) in the transformation of operational systems, with a dual focus: on the one hand, the optimisation of business processes; on the other, the evolution of urban governance in a smart framework. The initial hypothesis was that predictive, automated, and adaptive mechanisms developed within business contexts could be transferred—appropriately reinterpreted—to the urban systems of smart cities, thereby contributing to enhanced efficiency, sustainability, and the ability to proactively meet collective needs. The analysis conducted across the four chapters demonstrated that AI does not merely represent a technological advancement, but rather a structural shift in the very conception of processes, their management, and their legitimacy. In other words, AI today functions as a systemic enabler of transformation, whose most profound impact lies in redefining the relationship between operational efficiency, public governance, and the creation of collective value.

Throughout the study, it has become clear that the integration of AI in urban contexts is not solely a matter of technological or infrastructural capacity, but also a political, social, and ethical project that requires strategic vision, appropriate regulatory frameworks, and, above all, mechanisms for citizen participation and oversight. The adoption of AI introduces new opportunities but also new challenges: algorithmic opacity, informational asymmetries, dependence on proprietary models, and the risk of reproducing existing inequalities. In the face of these risks, cities are called upon to construct inclusive, transparent, and resilient civic architectures within which AI can operate in service of the public interest, and not merely technical efficiency.

The case study of Zurich demonstrated the practical applicability of these principles, highlighting both the strengths of advanced AI integration in urban systems and the areas where critical issues remain. Despite the positive outcomes in mobility management, energy optimisation, and predictive maintenance, challenges persist with regard to digital participation, equitable access, and the full inclusion of citizens in decision-making processes supported by intelligent technologies. This suggests that the transition to smart cities cannot be linear or definitive but must remain open to continuous adaptation, critical monitoring, and the inclusive redesign of solutions.

The survey conducted reinforced these findings, revealing a generally favourable attitude towards AI adoption, yet accompanied by specific expectations: transparency in automated decisions, ethical use of data, and the orientation of technologies toward collective well-being. As clearly emerged, citizen trust is not an inherent condition but one that must be actively constructed through regulatory, communicative, and cultural instruments capable of rendering technological processes intelligible, comprehensible, and contestable.

Overall, the findings of the thesis support the argument that, when managed with awareness, AI can become a foundational pillar of future urban development. However, it will not be computational power that determines the intelligence of cities, but rather the social and institutional architecture into which such systems are embedded. The future of urban AI will depend on the ability of institutions, communities, and individual citizens to design and govern technologies that reflect and uphold democratic values, social cohesion, and distributive equity.

For these reasons, it is recommended that future research focus on the comparative analysis of urban models in different geographical and cultural contexts, as well as on the evolution over time of public perceptions toward AI. It will also be essential to explore the relationships between intelligent technologies and urban inequalities, investigating how AI can contribute not only to service optimisation, but also to the promotion of a more inclusive, informed, and participatory form of citizenship.