Leveraging Meta AI, Spatial AI, and Character AI Model for Generative Smart Cities

Lee Kent
University of Tokyo
lee-kent@iis.u-tokyo.ac.jp

Tolga Karayel
University of Turku
tolkar@utu.fi

Youichiro Miyake
University of Tokyo
miyakey@iis.u-tokyo.ac.jp

Tero Villman
University of Turku
tero.villman@utu.fi

Abstract

Cities are complex, dynamic environments, requiring huge numbers of services and systems to facilitate and better the lives of the citizens within them. Keeping up with the demands of modern life has led to the creation of Smart City Digital Twins (SCDT), which are complete and bidirectional Cyber-Physical Systems (CPS) acting as observation and control mechanisms. Current SCDTs are typically bespoke implementations, catering to the city's unique needs and footprint. Generative AI will enable the generation of broader possible visions of the city, but the current data created by SCDTs is insufficient to train generative AI. This is a common problem for AI, and synthetic data is utilised to augment the training set. This paper proposes a novel concept for the creation of synthetic data; the use of the Meta, Character, Spatial Artificial Intelligence (MCS-AI) Model to emulate and therefore build the vast amounts of synthetic data required for a City Generative AI.

Keywords: Smart City Digital Twins, Generative AI, Synthetic Data, Cyber-physical Systems.

1. Introduction

A smart city can be conceptualized as a high-tech intensive and complex system that leverages new technologies to connect people, information, and city components, resulting in a more sustainable and greener city facilitating competitive and innovative business, and improved living quality. Further, Zheng et al. (2019) distinguished between narrow and wide definitions. The narrow digital twin contains virtual information that fully represents a physical entity, whereas a broad digital twin combines virtual and physical spaces as a Cyber-Physical System (CPS) (Möller, 2016).

Accordingly, Smart City Digital Twins (SCDT) can be described narrowly, as a virtual representation of city systems connected with Internet of Things (IoT) and sensor technologies; and broadly, they can be seen as complex socio-technical Cyber-Physical Systems (CPSs) where real-time data and autonomous actions are bidirectional between both physical and cyber entities (Karayel et al., 2024). While the physical entities can refer to spatial sentience, individuals, goods, or services in physical space; virtualized goods and services accumulation, characterized individuals and city systems via synthetic data can refer to cyber entities representing their physical counterparts. The articulation of digital twins, which are still experiencing the maturity period, to the phenomenon of smart cities, which continues to develop, is made more possible with today's Artificial Intelligence (AI) technologies. However, to address future challenges, holistic approaches need to be incorporated into research and business discourses.

New approaches are still needed because (1) high-tech intensive ICT infrastructure investments for the smartification of city systems are diversified and necessitate consideration of city needs (Finger & Razaghi, 2017; Lehtola et al., 2022) (2) businesses still have old business models which are mostly based on vendor lock-inns via patents for competitive advantage (Dignan, 2020; Hämäläinen, 2021) and (3) closed non-interoperable Application Programming Interfaces (APIs) with other city-systems (Fuller et al., 2020; Karayel et al., 2024). From a citizen's perspective, there are also privacy concerns, individual data, and enmity to privatization of data collection, processing, and commercialization by private third parties (Nochta et al., 2021). The remedy for these challenges could be the use of Generative AI (GenAI) based on synthetic training data that is able to preserve human agency while addressing the concerns.

GenAI provides substantial benefits to the difficulties experienced during the implementation of CPS solutions in smart cities (Muthumanikandan et al., 2023). For example, Ma et al. (2020) and Alwan et al. (2022) highlight the challenges of obtaining accurate, real-time data to model CPSs in smart cities and emphasise that synthetic data generated for GenAI can help bridge these gaps. Further, Singh et al., (2023) and Puliafito et al., (2021) point out, the collection of real-world data in CPS applications,

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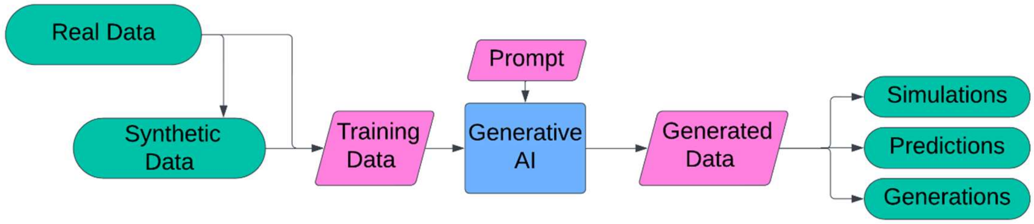

Figure 1. Synthetic data and its role in generative AI.

processing and using it on platforms that are vulnerable to cyber threats often raises privacy concerns among citizens. GenAI, on the other hand, can create synthetic datasets that mimic the statistical characteristics of real data without compromising privacy, so they can be used for testing and training without exposing sensitive information. However, due to the financial and systemic transformation burdens on cities to integrate CPSs into their existing urban systems, the scalability of existing data collection, processing, and information generation systems is limited. The demand to generate large volumes of synthetic data from existing data sets is sought in scalable solutions in smart city applications. In this regard, GenAI-enhanced CPS can optimize and improve decision-making addressing those challenges such as, energy consumption, and emergency response in cities (Puliafito et al., 2021), environmental governance (Bibri et al., 2024), generating synthetic data on urban mobility (Papyshev & Yarime, 2021), and sensitive greenery measurements (Biljecki et al., 2023)

The significant challenge of collecting sufficient training data is typically resolved using synthetic data, artificial data that is generated by simulations and algorithms rather than collected from real-world events or observations. The Meta, Character, Spatial Artificial Intelligence Model (MCS-AI) is a novel approach, grounded in video game development, in which these simulations and algorithms can be abstracted and simulated as dynamic agent-based systems (Hasegawa et al., 2017; Miyake, 2020). To advance digital twins for smart cities, this study suggests a new approach that combines the MCS-AI model with Cyber-Physical Systems thinking.

The potential of a GenAI that can create prompt-based cities resembling but not recreating our real cities is substantial. A GenAI, however, requires vast amounts of training data. There is simply not enough real-time data for our purposes, and therefore synthetic data is required. Figure 1 demonstrates the relationship between real data, synthetic data and GenAI.

This paper will consider the MCS-AI model against a CPS model to form a novel conceptual model for an end-to-end generative city paradigm. This is a different approach to SCDT, in which a single, continuously updating system is made to reflect a real city. The proposed approach generates prompt-based cities, as well as providing an opportunity to repurpose the real and synthetic data as agents operating within the generated cities for dynamic simulation, see Figure 1 and Figure 6.

2. Theoretical Background

In this section, the challenges and opportunities across four domains will be presented. Smart Cities are initially detailed (Section 2.1), and then considered as Cyber Physical Systems (Section 2.2). With a discrete amount of real-time data available to CPS systems, the use of Generative AI to create prompt-based visions of smart cities is described in Section 2.3. In the final section, 2.4, the MCS-AI model is considered as a framework to create synthetic data.

2.1 Smart Cities

While cities are homes for most humans now and increasingly in the future (UN-Habitat, 2022), they are also dynamic environments, melting pots of cultures, and cradles for innovations facing economic, environmental, and social challenges. For example, cities keep on growing due to urbanization, polarization creates social divides, climate crisis demands actions, economic downturn impacts the flow and availability of capital on all levels, growing ageing population require more services, and cities are expected to utilize new technologies to improve city services and liveability overall. Thus, cities need to find solutions to become 'smarter'.

Oftentimes, in the context of cities, 'smartness' is pursued with the utilization of information and communication technologies (Albino et al., 2015). Technologies are indeed a key enabler of smart cities and without technology, it is hard to achieve smartness, but smart cities involve much more than technologies. For example ISO (2018) emphasise the requirement of a smart city to use data information and modern technologies in order to deliver better services and increase the quality of life of its citizens.

In the pursuit of smart city development, six approaches have been observed. *Technocentric*: Using

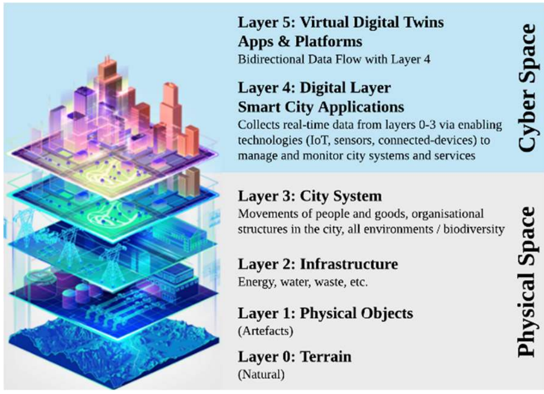

Figure 2. Cyber-physical Systems Thinking in SCs Graphics: esri.com.

technology to create connections between the city and technology. *Human-centric:* Citizen and participatory approach to steer urban development. *Organisation-centric*: Bringing forward economic strategies to ensure the city is both attractive and competitive. *Hybrid:* Combinations of the above three. (T. Singh et al., 2022). *Sustainability:* Using longevity as a metric for decision-making (Toli & Murtagh, 2020). *Holistic systems thinking:* Conceptualising smart cities as complex and dynamic sociotechnical systems (Kitchin, 2022).

While there are many approaches and in general a lack of agreement on an exact definition for smart cities, six dimensions have been used to assess smart cities: smart economy, smart environment, smart mobility, smart people, smart governance, and smart living (Lombardi et al., 2012).

2.2 Cyber-Physical Systems (CPS)

CPSs refers to real-time networks of physical and cyber spaces. CPSs requirements vary according to the application domain and have various definitions and conceptual approaches. Nonetheless, with a domain-agnostic holistic perspective, CPSs consist of three main components (Gunes et al., 2014). These refer to the physical world and systems (e.g., humans, cars, energy grids, road infrastructure, and water systems), digital infrastructure (IoT, sensor technologies, etc) and cyber systems. In CPSs, physical entities can be monitored and controlled with cyber systems through embedded computing and sensor technologies, with bidirectional data flow. Further, Möller (2016) emphasizes that CPSs are systems of systems in which collaborative computing elements collect data and in return control physical entities in real-time with IoT and big data, enabling autonomous behaviours. CPSs provide such core services as control, feedback loops and real-time monitoring (Möller, 2016).

Increasing digitalization, climate change and urbanization put pressure on urban systems and make CPSs offering significant potential benefits, however, it also brings with it budget and infrastructure challenges, especially for the collection of sufficient data, privacy, security, scaling, and integration into existing city systems (K. D. Singh et al., 2023).

Figure 2 shows a typical representation of a city as a CPS and is described through the following layers (Lu et al., 2019; White et al., 2021). *Layer 0*: The terrains on which they are located. *Layer 1*: Physical objects/artefacts, e.g. buildings, bridges, power plants, people and vehicles. *Layer 2*: Infrastructure such as energy, water and waste systems that connect all these artefacts. *Layer 3*: the integration of all these systems in the physical environment. *Layer 4*: Equipping these physical systems with ICT tools such as sensor technologies and IoT. *Layer 5*: Digital twin applications and platforms are connected to a Smart City with bidirectional data flow.

There are several components to transforming conventional city mobility services into smart city systems, which can be briefly summarized as adequate infrastructure (ICTs), technical know-how on unique system-level requirements, and building coordinated real-time CPS networks (Ahmad et al., 2021; Gunes et al., 2014). The integration of CPSs into existing city systems presents challenges such as data heterogeneity, integrity, and real-time sensing and parsing, along with obtaining data for precise modelling (Alwan et al., 2022; Ma et al., 2020). The challenges of detecting patterns from the imbalanced and complex data sets of existing urban systems provide a strong argument for the use of synthetic data (Čech et al., 2024).

2.3 Synthetic Data and Generative AI

GenAI is a subset of AI that is focused on the creation of new content that is independently original, but statistically resembling examples from within the training set (Feuerriegel et al., 2024). GenAI can be multi-model, able to receive prompts in the form of text, images, audio etc, and interpret them to generate previously unseen content (Brynjolfsson et al., 2023). The datasets required in the creation of these generative models is diverse and vast, and the training process is typically an opaque statistical interpretation of patterns and structures within the training data, so that inputs may be tokenised against learned patterns.

GenAI is showing proficiency in natural language processing and computer vision which has led to quantifiable benefits for productivity and outputs (Noy & Zhang, 2023; Peng et al., 2023). GenAI can be used to generate text such as articles or stories, or converse with a user as a virtual assistant (Brynjolfsson et al., 2023), and to create more complex media, such as images, audio, and video.

GenAI typically requires vast amounts of training data to identify patterns, and there are many challenges with aggregating this data including fragmented approaches, data interoperability, concerns over privacy, and a reliance on commercial third parties for platforms (Almirall et al., 2022). Accumulating enough real-world data to train a city-scale GenAI is currently unfeasible. To address this, training data can be partly comprised of real-world data, but a more significant portion can be synthetic data (Almirall et al., 2022).

Synthetic data is artificially generated data to supplement training data (Čech et al., 2024; Lee et al., 2023). The synthetic data required here needs to be multi-dimensional, realistic, dynamic, responsive to multiple agents with different and possibly conflicting goals, with systems that affect and target individuals and groups, optimised to operate in real-time with a fundamental holistic objective of creating an engaging world simulation. Essentially, these requirements mirror the complexity found in video game design.

The strengths of Game engine technologies, such as high-fidelity 3D scene rendering and optimization, have previously been leveraged as part of synthetic dataset creation pipelines (Kent et al., 2023; Lee et al., 2023). These engines are designed to create user-centric, positive experiences, directly addressing the challenges discussed in the previous section. By using game engines and game design processes for synthetic data creation, the focus shifts from mere geometry and system modelling to a user-centric approach, capturing and emulating user interactions with game environments and systems.

2.4 Meta, Character, Spatial AI Model

A key feature of game engines is their ability to integrate various systems and types of AI into a bespoke and dynamic environment (Hasegawa et al., 2017; Lefebvre, 2018). This integration can control the behaviour of agents such as non-player characters or to create responsive systems such as progression systems (Miyake et al., 2020; Miyake, 2020). A general theory of game AI that is used in large-scale games utilises three types of AI; Meta AI, Character AI and Spatial AI, called the MCS-AI model (Miyake, 2020). These AI work together to dynamically respond to player input.

Character AI represents autonomous entities within the game, such as NPC (Non-Playable Characters) allies, or adversaries. These agents possess their own goals, urgencies, capabilities, and interactions (Park et al., 2023), allowing for increasingly complex and realistic behaviours (Hasegawa et al., 2017; Miyake, 2020). Notably, humans can be considered a type of agent within this framework, sharing a subset of capabilities and goals. The concept of Character AI can extend to applications like virtual assistants, where the AI exhibits sophisticated, human-like interactions.

Spatial AI is concerned with the game's 3D components. Character AI has specific objectives, but Spatial AI realises how to achieve them. It manages how space is captured, stored, and presented. Spatial AI has oversight of systems such as the navigation mesh, by dynamically determining the traversable areas. This component is crucial for ensuring that the game world is functionally coherent, and can control scene components, allowing for seamless interactions between the player and the game space (Miyake et al., 2023). Spatial AI's ability to handle detailed and dynamic environments makes it a vital element in the development of both games and smart city simulations, where accurate spatial data is essential.

Meta AI oversees the overall flow of the game, directing progress, making queries, and coordinating changes across the other AI agents (Lefebvre, 2018; Miyake et al., 2020). This ensures that the experience remains engaging and coherent, adapting to the player's actions and decisions. In the context of smart cities, Meta AI can play a crucial role in managing and optimizing urban systems, ensuring efficient and responsive interactions between various city systems.

The combinatorial and cooperative use of agents within this framework ensures that the experience for the player is consistent and engaging, Figure 4 highlights how the agents that comprise the MCS-AI model may be reframed as agents within a digital twin of a smart city.

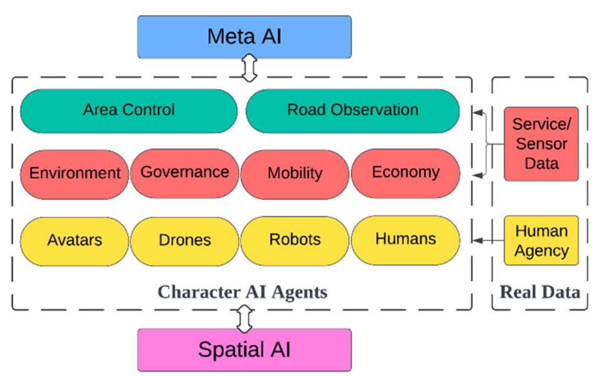

Figure 3. The MCS-AI model, framed as agents and systems within the digital twin of a smart city.

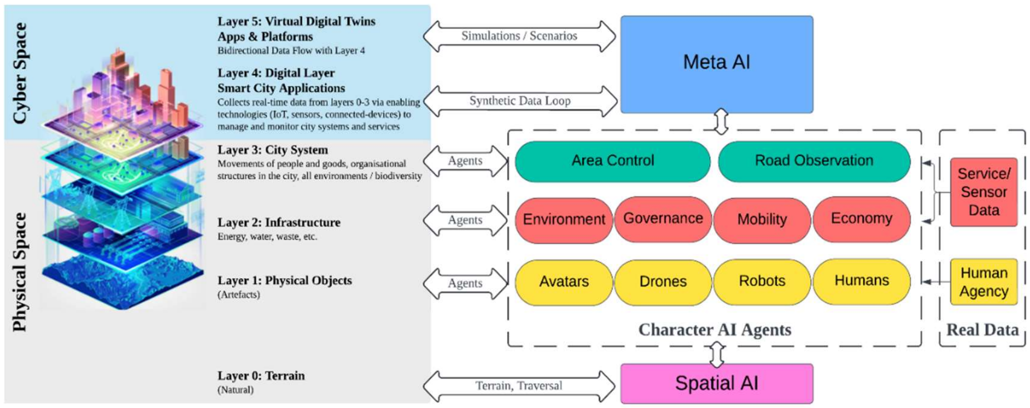

Figure 4. Reflecting the MCS-AI model against the CPS model of a Smart City.

2.5 Summary & Opportunity for Research

A fundamental challenge for creating smart city digital twins is that each city is unique, with its own cultural, architectural, and historical footprints that necessitate sensitive and unique approaches to digital representations. The MCS-AI model offers a framework for agents that enable complex experiences. By leveraging the capabilities of the agents, urban environments can be emulated dynamically. Further, permutations of city geometries, agents and systems can be aggregated and emulated to create synthetic training data for a GenAI with the ability to generate prompt-based cities resembling but not recreating real cities.

3. Conceptual Developments

The CPS and MCS-AI model are presented together in Section 3.1 and are described further in Section 3.2 in terms of the agents that could represent them, and how this will lead to the building of synthetic datasets. In Section 3.3, how human agency can be represented within the synthetic data is considered. Section 3.4 describes how the new concept model can support a Generative AI framework, and Section 3.5 presents the privacy and ethical considerations.

3.1 Overlapping CPS and MCS Models

The first step is to unify the two models. CPS provides the current framework of a smart city, delineating the processes, systems, geometries, devices etc, that are required for a digital twin. In Figure 4, the MCS-AI model can be considered a reflection of layers 0-4 of the CPS model, providing a structure in which they can be completely virtualised.

Spatial AI represents all the physical and three-dimensional components within the space. This is a clear parallel with Layer 0 and Layer 1, which comprise terrain and physical objects. Spatial AI, whilst not generating new terrains and physical spaces, is concerned with how to react within them, providing information such as dynamically determining navigable areas, weather information and route planning.

Layers 2-4 are wholly represented as various forms of Character AI. Character AI can be seen both as physical representations of entities with autonomy, such as autonomous vehicles and humans, but also as digital services and systems of systems. A character AI is for specific tasks, such as measuring utilities or emulating services. Fundamentally, if an object is not spatial (physical or terrain), then it is represented by a Character AI. Figure 5 gives examples of experiences that facilitate emergent behaviours due to the autonomy of the agents.

The Meta AI has two specific roles in our new conceptual model. The first role is the ‘classical’ role, in that it oversees the flow of the entire city simulation, measuring global parameters, city-wide and community agendas, as well as acting as an observation and command centre for Character and Spatial AIs. The second role is to be the interface between the GenAI and the Training/Generated Data. The prompt given to the GenAI should impact the simulation and parameters of the generated city. This can be achieved through the Meta AI, as every other agent within the system will regularly poll the Meta AI for information and direction.

From Figure 4, each AI agent within the system will have very specific roles, goals and parameters. It is envisioned that every agent within the synthetic dataset will reflect an artefact, process or system of

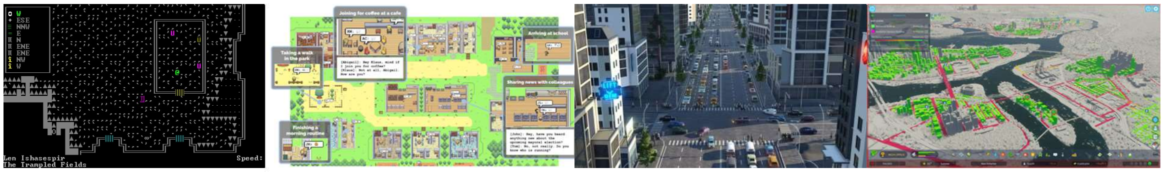

Figure 5. Emergent behaviours from agent interactions in dynamic worlds. (Left to Right) Dwarf Fortress, Interactive Simulacra (Park et al., 2023), Transport Fever, and Cities Skylines II.

‘real data’ from a smart city digital twin. As the capability and amount of real data increases, the amount of synthetic data available increases manifold.

3.2 Creating Synthetic Datasets

In the creation of synthetic datasets, there are two sources of inspiration to draw from. The real data from digital twins of cities, and from the process of creating video game cities. The creation of synthetic data will be discussed layer by layer using the CPS model.

Not all layers require AI in terms of dynamic cooperative agents. For example, in Layer 0 and most of Layer 1, the terrain and buildings can be procedurally generated. The topography of the space can be dynamic, and there are many tools able to facilitate this.

Once the typically more static physical objects are defined, the space can be populated with real-time and dynamic objects with agency. Across Layers 1-3 Character AI is used to replicate all manners of services, infrastructure, vehicles, and people. Video games often use agents with Character AI, shown in Figure 5 and the capabilities can be seen as analogous to our digital twin domain.

As each agent attempts to achieve its objectives, the interactions between agents allow for emergent and unscripted events and situations. For example, many agents try to reach the same distant objective, then transportation systems become overwhelmed, and other agents will be affected and will need to use alternative transportation routes and methods. These emergent situations are monitored and reported to the Meta AI. Figure 5 shows several kinds of AI implementations that facilitate emergent events. The following section, Section 3.3, will describe human representation as Character AI.

If we look to current cutting-edge city creation, simulation and planning tools both functional and for entertainment, there are many approaches and interoperable systems, a range of which are presented in Figure 5. The advantage of the MCS-AI model is that the agent operates independently of other agents, and if information is required, Meta AI is polled which is city instance specific. It is due to this centralised control of city-wide parameters that the Meta AI becomes the interface, both for the creation of training data and for the Generative AI. This interface will be described further in Section 3.4.

3.3 Capturing Human Agency

Arguably, the most important agent within the city generation is the creation of human proxies. Human agency can be captured either with a bottom-up or observatory approach. In the first bottom-up approach, a single and highly representative character AI is used to emulate the many immaterial facets of a person, such as their goals, desires, skills personality, fallibilities, and memories. Large Language Models (LLMs) have been shown to be a powerful tool in achieving this, able to log and act on prior experiences.

An alternative approach is to capture the person as a function of their interactions within the smart city. By creating agents that replicate the services and systems of a city, their capability, capacity and loads can also be synthesized. In this approach, humans do not need to be directly measured, alleviating privacy concerns. An example of this is measuring building or room occupancy via sensing entrances, rather than the specific people inside them.

3.4 A City Generating AI

In Figure 1, we introduce a diagram describing the relationship between real data, synthetic data and generated data. In Figure 6 we highlight how the MCS-AI model can be utilised to both enhance the creation of synthetic data and AI-generated cities.

As before, real data is the foundation of the model. The agents within the MCS-AI model must be grounded in reality, or the AI generations will have no grounding in reality. The agents then exist within city simulations, with the Meta AI logging interactions to match the structure of the ‘real data’. In doing so a much larger set of training data is created, that has a significant portion of synthetic data.

Many models and methods of GenAI development to create synthetic data from existing data sets are available, but the most popular known method is Generative Adversarial Networks (GAN) (Pandey et al., 2023). GANs have two parts; a

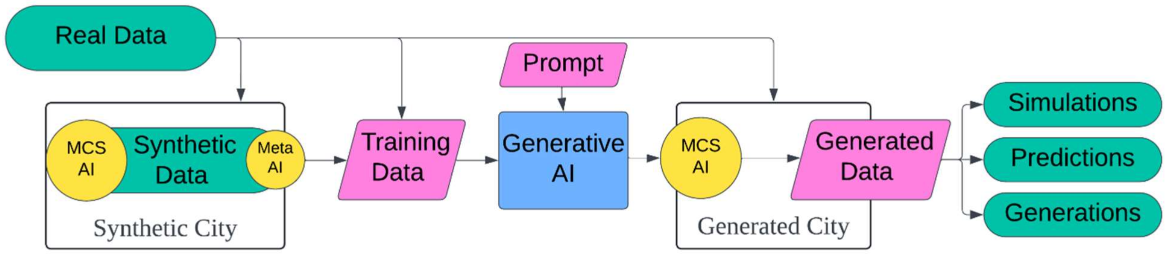

Figure 6. Embedding the MCS (Meta Character Spatial) AI model into a Generative AI Paradigm.

generator that produces synthetic data and a discriminator evaluating its authenticity and refines the generator's outputs through iterative training (Čech et al., 2024). GAN-based GenAI approaches are capable of successfully generating high-quality synthetic data by managing both static and temporal dynamics to optimize AI-driven systems in real-world environments (Pandey et al., 2023).

Developing GenAI for smart cities presents several significant challenges. The complexity of real-world data, privacy concerns, and the need for large, high-quality data sets are primary barriers (Čech et al., 2024). There is a challenge with creating synthetic data that can reflect real-world conditions without sacrificing privacy, the high computational demands of training on the temporal dynamics of city data and addressing data imbalances and on large-scale datasets of urban systems pose more difficulties (Pandey et al., 2023). Restrictions on GenAI development methodologies with such models as GAN can lead to inaccuracies in synthetic data-based estimates (Čech et al., 2024; Pandey et al., 2023). Thus, especially in smart city CPSs effective implementation of new AI-driven potential solutions in smart cities is crucial.

The Meta AI observing and controlling the newly generated City is now simulated against the prompt. The agents created for the synthetic data can be integrated into the newly generated city. As they poll the Meta AI, the instructions and city will be motivated by fulfilling the parameters of the prompt.

3.5 Privacy, Security, and Ethical Concerns

Collection of real-time citizen activity data introduces both privacy and security implications that must be considered, and effective processes to do so are one of the main SCDT challenges (Fuller et al., 2020). Evolving regulation and federated learning with decentralised Machine Learning frameworks, as well as the use of blockchain, have all been proposed to ensure citizen privacy is respected and the security and integrity of the data are ensured (Nguyen et al., 2024).

There are further ethical implications for this proposal, particularly when considering the use of synthetic data and GenAI for decision-making. The data is not truly reflective of reality, as it is not a true digital twin, instead creating a vision for a proposed reality that statistically reflects the training data that only partly comprises real data. Statistical modelling and forecasting are often used for decision-making, occasionally inducing automation bias, however, there must be trust in the quality and accuracy of the generated cities. An advantage of this approach is the reduced need to capture real-time data and the anonymised nature of the captured real-time data. Instead of tracking a person for the purposes of personalisation, a service or sensor data is captured.

4. Smart Mobility

Previously, six dimensions have been used to assess smart cities: smart economy, environment, mobility, people, governance, and living (Lombardi et al., 2012). This paper narrows the scope to the dimension of Smart Mobility. Table 1 highlights many applications in which GenAI can support smart cities.

GenAI provides potential benefits for various applications of smart mobility by generating synthetic traffic data for route management, autonomous vehicle development, and road infrastructure planning (Xiong et al., 2015). When considering the range of components such as infrastructure and vehicles, traffic lights and roadways in the integration of CPS systems, Gunes et al., (2014) emphasized that this does not only depend on sensors and embedded computers, but also requires better communication protocols between Vehicle-to-Vehicle (V2V), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Infrastructure (V2I) to manage complex traffic systems.

4.1 Applying the MCS-AI Model

Converting the model posed in Figure 6 to be applicable with the MCS-AI model requires reframing the system. Everything effectively becomes

Table 1. Applications of Generative AI (GenAI) in smart city mobility CPSs.

CPSs in Smart Mobility	Application of GenAI	Synthetic Data Generation
Traffic Flow Org	Simulating scenarios.	**Adaptive Traffic Signal Systems** Generate real-time traffic conditions. (V2I)
Autonomous Vehicle (AV) Testing and Deployment	Generating realistic synthetic data for training and testing AV algorithms.	**Simulation Environments** Generate detailed simulation environments that mimic complex urban scenarios. (V2I) **Scenario Generation**: Generate diverse driving scenarios, such as interactions with pedestrians, cyclists, and other vehicles. (V2V – V2I – V2P)
Public Transportation Systems	Providing synthetic data-driven insights that improve efficiency and service quality.	**Demand Forecasting**: Generate future scenarios, AI can forecast passenger demand for public transportation. (V2V – V2I) **Route Optimization**: Generate alternative routes for public transport and their impact on travel times and passenger satisfaction. (V2V – V2I – V2P)
Infrastructure Planning and Development	Planning and developing infrastructure by providing detailed simulations and predictive analytics.	**Road Network Design**: Generate and evaluate different road network designs and their impact on traffic flow and safety. (V2I) **Smart Parking**: Generate capacity, demand patterns and optimizing the allocation of parking spaces. (V2I)
Emergency Response and Management	Simulating various disaster scenarios and their impact on urban mobility.	**Evacuation Planning**: AI-generated synthetic data can model evacuation scenarios, helping city officials plan efficient evacuation routes and strategies **Incident Management**: GenAI can simulate traffic incidents and their consequences, enabling authorities to develop rapid response plans that minimize disruption and restore normal traffic flow swiftly. (V2V – V2I – V2P)
Ride-Sharing and Mobility-as-a-Service	Providing predictive insights and enhancing operations.	**Demand Prediction**: Generate ridesharing demands **Route Matching**: Generate ridesharing scenarios to improve route matching

centralised through the MCS model. Vehicles become agents with Character AI. Each vehicle has unique characteristics, capabilities and constraints. A vehicle will have onboard functions such as to avoid imminent or unexpected collisions, but things like route planning or knowing the objectives of other vehicles are not important. Spatial AI controls the flow of all vehicles, each Character AI only needs to fulfil its own purpose.

The Meta AI facilitates the observations and commands agents so it may achieve its objectives. Meta AI requests route planning and information from Spatial AI. Spatial AI watches 3D space in real-time, so is also determining safety issues such as potential collisions, traffic buildup avoidance etc. In games Spatial AI typically controls things like navigation meshes (space traversal capabilities) and multi-agent optimum and realistic route planning, avoiding collisions.

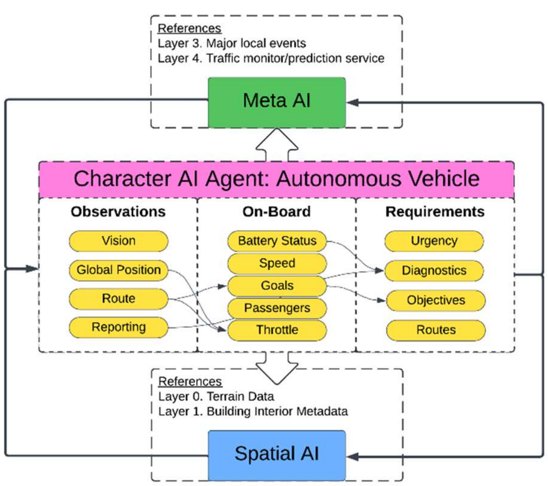

Figure 7. An Autonomous vehicle framed as an MCS-AI model agent.

4.2 Data Structure and Integration

The data structure of the agents will follow conventional game engine structures and design patterns, such as encapsulation, state machines, and event queues. The implementation will vary for each agent and SCDT taxonomies can be used to determine the specific data structures.

Figure 7 is an example agent, an autonomous vehicle with Character AI. *Observations* can come from three sources, real data, synthetic data, or from Meta AI. The *on-board* components are the states and possible actions of the agent. The agents' *requirements* are their interactions with the Meta and Spatial AI, for example, to set objectives, urgency and request optimal routes to achieve the agent's goal.

The Meta AI in this instance can look to CPS Layer 3 for traffic patterns or major local events that will impact route planning. The Spatial AI has specific knowledge of route options from CPS Layers 0 and 1 as well as route processing capability (Miyake et al., 2023). This example shows how the CPS model of a smart city supports an agent-based approach to modelling a smart city, which in turn facilitates the use of the MCS-AI model that can be used to create and capture synthetic data.

5. Conclusions

The value of a city-level GenAI, one that can create and simulate prompt-based visions of existing and imagined cities has significant implications for citizen participation, government officials, planners, decision-makers and many more. With the recent advances in Large Language Models and Vision-based generative models, it seems inevitable that these models will soon move towards being able to generate dynamic and 3D spatial data.

To achieve this, however, vast amounts of synthetic data grounded in real data are needed. There are many examples of Smart City Digital Twin (SCDT) endeavours. This paper has proposed the novel concept of applying the Meta, Character, Spatial AI model utilised in game development to the SCDT model, providing a new opportunity to create synthetic data. Smart Mobility was presented as a value stream for SCDT, and how this would be reframed as an MCS-AI model was considered and the potential for synthetic data creation was presented.

Building on this conceptual paper, empirical research is needed to validate and verify the developed model. Smart Mobility was presented as a value stream for the potential integration of smart city CPSs and MCS-AI model for synthetic data creation. In addition, other smart city domains can provide new avenues for further research.

6. References

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