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A digital twin smart city for citizen feedback

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ABSTRACT

A digital twin is a digital representation of a physical process, person, place, system or device. Digital twins were originally designed to improve manufacturing processes using simulations that have highly accurate models of individual components. However, with increasingly large and accurate building information models (BIM) combined with big data generated from IoT sensors in a smart city, it is now possible to create digital twin smart cities. An accurate 3D model of a city can be published online and walked around by the public to view proposed changes in urban planning and policy. This allows for easier dissemination and transparency to the public before putting these decisions into practice. This open and public model allows for an additional virtual feedback loop where citizens can interact and report feedback on planned changes in the city. Citizens can also interact with components to tag and report problems in their area. The digital twin also allows for additional experimentation where 3D data is necessary, such as flood evacuation planning. In this paper, we demonstrate a public and open digital twin of the Docklands area in Dublin, Ireland and show how this model can be used for urban planning of skylines and green space allowing users to interact and report feedback on planned changes.

1. Introduction

Cities have become increasing smarter in the last two decades (Albino et al., 2013), using pervasive information and communications technology (ICT) to monitor activities in the city (Neirotti et al., 2014). Data can then be generated from a wide variety of activities in the city, such as traffic and transportation (Menouar et al., 2017), power generation (Oldenbroek et al., 2017), utilities provisioning (Sánchez et al., 2013), water supply (Parra et al., 2015) and waste management (Medvedev et al., 2015). Smart cities can then use this data to improve the mobility, environment, living standards and governance of the city (Abella et al., 2017; Angelidou, 2015). A strong link has been shown between investing in smart city policies and urban GDP growth (Caragliu & Del Bo, 2019).

The data generated by smart cities makes them exciting testbeds for data mining and machine learning (Mohammadi & Al-Fuqaha, 2018; White & Clarke, 2020). The services provided to citizens in a smart city can be personalised using machine learning, internet of things and big data (Chin et al., 2017; White, Palade, et al., 2019). These deep learning algorithms can be used to categorise and perform analytics on a number of different data streams including videos (Wang & Sng, n.d.). More recent neural network approaches, such as generative adversarial network (GAN) can be used to optimize crowd routing in a smart city (Zhao et al., 2019). In the digital twin layer reinforcement learning algorithms can also be used to learn the best action policies to improve performance in a number of urban intelligence tasks, such as managing traffic and power systems (Hsu et al., 2014; Mannion et al., 2016).

The increased data available from smart cities, artificial intelligence, data analytics and machine learning allows for the creation of a digital twin that can update and change as the physical equivalents change (Kaur et al., 2020). A digital twin is a pairing of the virtual and physical worlds that allows for analysis of data and monitoring of systems to head off problems before they occur, prevent downtime and can even be used to plan for the future using simulations (Boschert & Rosen, 2016). Digital twins have primarily been used in the manufacturing sector, but other areas of study and business are beginning to find new potential uses. An ideal digital twin would be identical to its physical counter-part and have a complete, real-time dataset of all information on the object/system. As the object/system increases in complexity a digital twin may be identical in only relevant areas and have only the real-time data necessary to support any desired simulations. How accurate and useful a digital twin is, depends on the level of detail put into it and how comprehensive the available data is.

Digital twins allow for the simulation of many options before taking physical action in the real world to identify the strengths and weaknesses of each plan. This is especially important in safety critical

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situations, where only one option can be chosen and there may be a number of competing plans to choose from. This is exemplified by the rescue operation in Thailand to save a lost soccer team that occurred in July 2018 (Puri, n.d.) (Dixon, n.d.). A 3D map of the terrain, a complex cave system, was created using GIS data, water and oxygen information inside the caves. Weather forecasts were also used in order to create an accurate digital twin that could simulate rescue operations and ensure the safety of the rescuers and the lost team. The use of a digital twin ensured that when rescuers acted, it was a best-case scenario after testing multiple options.

Digital twins can have applications in a number of different domains. With the data generated by smart cities, digital twins can be used to model urban planning and policy decisions. An example of a work-in-progress digital twin of a city is Virtual Singapore,[1] which is a three-dimensional (3D) city model and data platform (Alam & El Saddik, 2017). In this paper, we expand on the digital twin ideas introduced in Virtual Singapore and make our model publicly available on the internet.[2] This allows users to easily interact with the model, leave feedback about urban planning decisions and tag problems in their local area. This generates an additional layer of data that can be used to make changes in a smart city. We also show how the 3D model can be used to create realistic flooding and crowd simulations.

In this paper, we present an open and publicly available digital twin smart cities model of the Docklands area in Dublin, Ireland. Section 2 presents the related work that has been conducted using digital twins in different domains. Section 3 presents the design of the digital twin smart city model and how it is created through the combination of data from a number of different layers across the city. Section 4 presents the experimental setup that was used to conduct the simulations and the feedback that was received by making the model publicly available. Section 5 presents the results of those simulations and Section 6 presents some of the limitations of the current digital twin model and how it could be improved in future iterations. Section 7 concludes the paper and presents some future work.

2. Related work

Digital twins are a digital replica of a living or non-living physical entity (El Saddik, 2018). Enabling tools for digital twin data, services, modelling and connection to the physical world have led to the increased popularity of digital twins (Qi et al., n.d.). Digital twins integrate internet of things, machine learning, artificial intelligence and data analytics to create living digital simulation models that update and change with their physical counterparts (Luo et al., 2019). A digital twin is continuously learning and updating itself from multiple data sources to represent the physical object in near real-time. The system can learn from itself, from other similar digital twins or from human experts with relevant domain knowledge. A digital twin can also learn from historical data in past usage and factor this into its digital model.

Digital twins were first defined by NASA as a paradigm for future NASA and U.S Air Force vehicles (Glaessgen & Stargel, 1818). A digital twin would allow for ultra-high fidelity simulation using data from the vehicle's on-board system, maintenance history and all available historical and fleet data to identify any possible problems in safety or reliability. They have since been applied to a number of manufacturing projects as they can bridge the gap between the virtual and physical space at different stages in the product's lifetime (Tao et al., 2018). A digital twin allows for the product to be tested at all stages of the design process to ensure the design is feasible, safe, efficient and reliable (Rosen et al., 2015).

A digital twin makes control and experimentation of a complex system feasible (Grieves & Vickers, 2017). This has led to them being used in a number of complex systems beyond product design and the manufacturing process. Digital twins can be used to create digital twin humans that can be used in healthcare (Bruynseels et al., 2018). With the rise of quantified-self, users can now collect more data about their physical activity, sleep quality, diet, heart rate, weight, productivity, working environment and social interaction (White, Liang, et al., 2019). This data can then be used to create an accurate digital twin to predict upcoming health issues as well as test solutions to prevent or reduce the damage of any complications (Bhavnani & Sitapati, 2019).

Digital twin cities can be created using the data collected from smart city services (Mohammadi & Taylor, 2017). The virtual representation allows for modelling and visualisation of the spatiotemporal information in a city. Much of the recent success in smart cities around the world in integrating reliable ICT systems into the city can be utilised to create a digital twin of a city (Mohammadi & Taylor, 2019; White et al., 2017). An initial attempt to create a digital twin smart city has been conducted in Singapore, also known as Virtual Singapore (Soon & Khoo, 2017). However, there are a number of limitations with this initial approach as the model has not been made publicly available, so citizens cannot interact with the model or report feedback and it does not include urban mobility data. Digital twin programmes are in the early stages with a roadmap being outlined at the Centre for Digital Built Britain at Cambridge University (Enzer et al., n.d.). The roadmap shows the key building blocks and actors that together would enable successful digital twins across the built environment. In this paper we tackle point 3.10 to undertake strategic pilots to prove the information architecture with selected stakeholders and point 4.7 to share learning from digital twin hubs, pilots and demonstrations.

A number of private companies, such as CityZenith,[3] Agency9 who were acquired by Bentley[4]and SmarterBetterCities[5] have started to develop in the Digital Twin Smart City space. However, all of these companies are private and do not make their models publicly available and charge expensive licensing fees. Our approach is publicly released on the internet allowing users to interact with the model and for it to be used in future digital twin projects for free.

In this paper, we create a digital twin of the Docklands area in Dublin, Ireland using a publicly released 3D model.[6] We show how the model can be used for a number of urban planning and policy decisions by adding a proposed building to the skyline as well as additional green spaces and parks. As the model is available online1 users can easily tag problem areas in the city and fill forms to make changes in their local area. This generates additional data that can feed back into the digital twin to specify problem areas in the city that need to be developed. We also show how our digital twin can be used to create a number of urban mobility simulations using pedestrian mobility, as well as simulating the effect that the river flooding would have on the city.

3. Digital twin smart city design

A digital twin smart city builds on a number of layers of information in the city. We define six layers in our digital twin smart city model, as shown in Fig. 1. The first five layers build on top of each other adding more information about the terrain, buildings, infrastructure, mobility and IoT devices in the city. The Digital Layer/Smart City is used to collect data from the city, which it can then pass to the Virtual Layer/ Digital Twin. The Digital Twin uses the data generated in the smart city to perform additional simulations about mobility optimisation, building placement or the design of renewable energy such as offshore wind turbines. This information is then fed back through the layers of the

[1] https://www.nrf.gov.sg/programmes/virtual-singapore.
[2] https://www.scss.tcd.ie/~whiteg5/webgl/.
[3] https://cityzenith.com/.
[4] https://www.bentley.com/en/products/product-line/reality-modeling-software/opencities-planner.
[5] https://www.smarterbettercities.ch/.
[6] https://data.smartdublin.ie/dataset/3d-data-hack-dublin-resources.

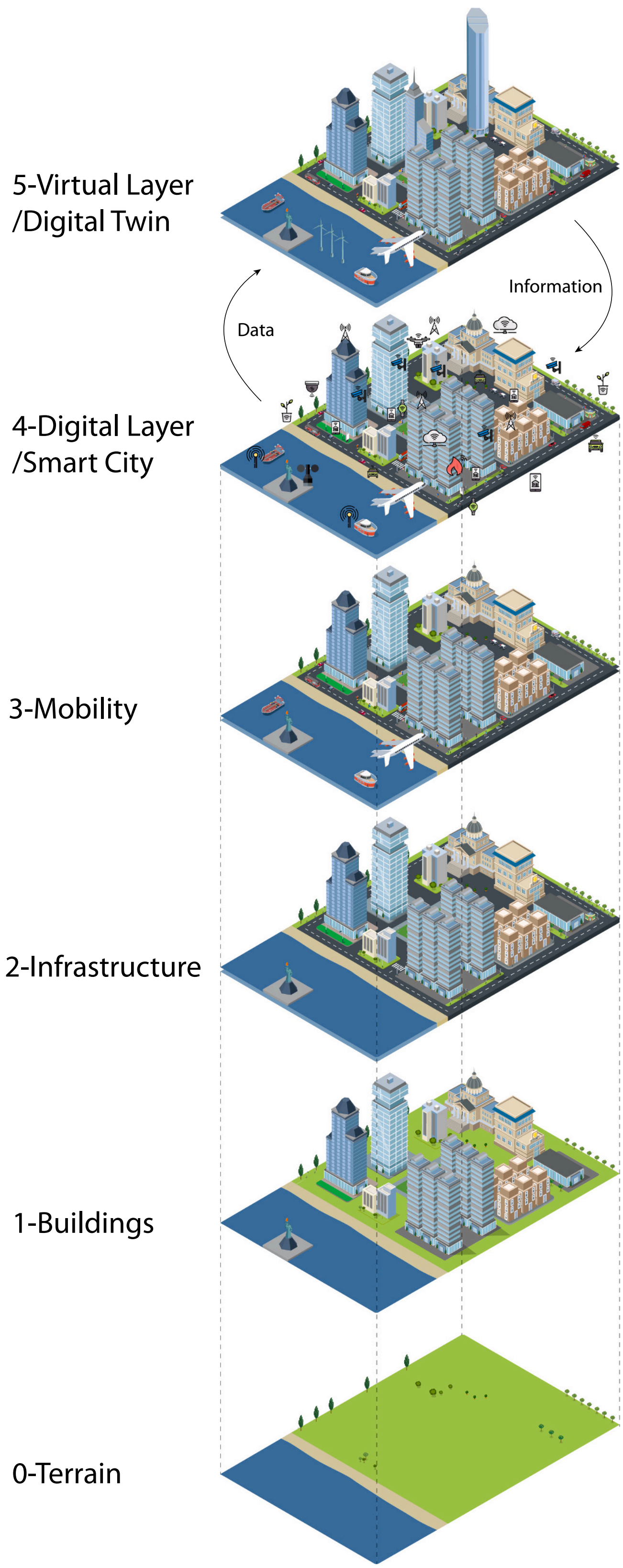


Fig. 1. Layers required to develop a digital twin smart city.

model where it is implemented in the physical world. In this section we describe each layer of the model as follows:

3.1. *Terrain*

The zeroth layer of the digital twin smart city design is the terrain on which the city is built. This is basic information about the city, such as what part of the city is offshore, are there rivers or canals running through the city, are there steep gradients or hills in the city, what part of the city is made of sand, what area of the city has fertile soil that can be used to grow crops, what areas of the city have soil with poor draining that can cause problems, such as a landslide or during heavy rain or flooding. A soil map, as show in Fig. 2 can be used to incorporate this information in the model.

3.2. *Buildings*

Layer 1 of the digital twin smart city model then adds the current buildings in the city to the model. These buildings have highly accurate building information modelling (BIM) models that can be used as a digital twin of the building. The 3D building data can also be generated using stereoscopic aerial photography. The building data used in our digital twin is of the Dublin Docklands district in Ireland. This data is publicly available as an FBX file2.

The data is limited to the area between the Samuel Beckett Bridge and the Eastlink Bridge. It contains the region two blocks north of the river and partially contains the region south of the river up to the end of the Grand Canal.

3.3. *Infrastructure*

Layer 2 of the digital twin smart city model then adds the infrastructure that surrounds the current buildings in the city. This is the basic physical and organisational structures and facilities (e.g. roads, power supplies, telecommunication) needed for the operation of a society or enterprise. This infrastructure data can come from OpenStreetMap, which contains information about power, public transport, motorways, highways, amenities and telecoms. Data can also come from the 3D mapping process to add gradient information as this may not be available in open street maps.

3.4. *Mobility*

Layer 3 of the digital twin smart city model adds mobility to the infrastructure and building layers. Mobility is the movement of people during their daily routing and the movement of the goods that help them in different aspects of their lives. Software applications such as SUMO can be used to simulate urban mobility (Lopez et al., 2018). SUMO simulator supports a number of different transportation modes: walking, bicycles, powered two-wheelers and generic parametrized vehicles. Additional available models are railways and waterways. This application can be connected to the 3D model in Unity using the Traffic Control Interface (TraCI). Unity can also be used to implement and enhance the traffic modes, adding additional behaviours that the simulator does not model. In our case, we are interested in adding multiple pedestrian types, such as adult and elderly.

3.5. *Digital layer/smart city*

The digital layer/smart city layer has become hugely popular with a number of projects focused on integrating IoT sensors in the city to collect data (Dameri et al., n.d.; Caragliu et al., 2011; Cocchia, 2014). This data can then be used to monitor and manage traffic and transportation systems (Menouar et al., 2017), power plants (Oldenbroek et al., 2017), utilities (Sánchez et al., 2013), water supply networks (Parra et al., 2015), waste management (Medvedev et al., 2015), crime

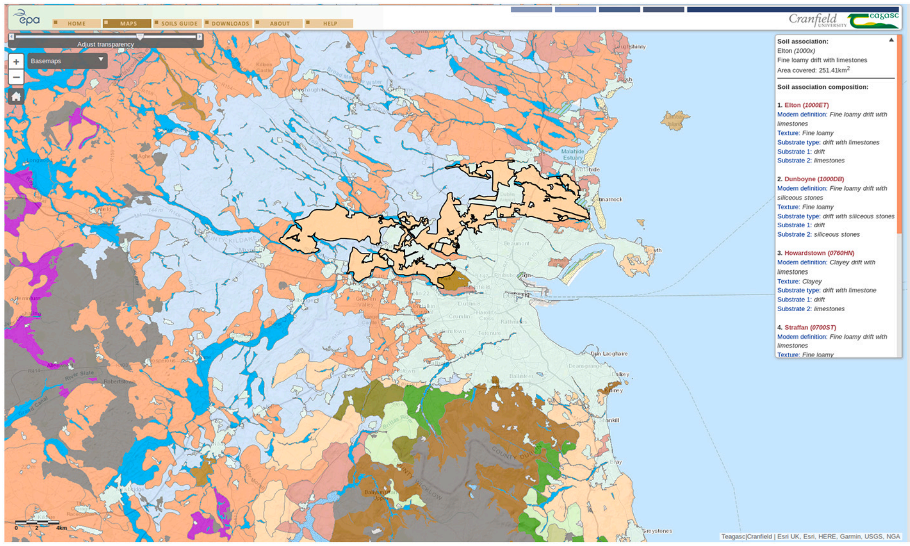


Fig. 2. Soil map.

detection (Chiodi, 2016), information systems (Abdel-Basset & Mohamed, 2018), schools (Williamson, 2015), libraries (Johnson, n.d.), hospitals (Pramanik et al., 2017), and other community services (Hashimoto et al., 2015; Jalali et al., 2015).

As shown in Fig. 1 layer 4, the digital layer/smart city is responsible for gathering all the data needed for simulations in the virtual layer/ digital twin, from all the previous layers. The results of these simulations are then fed back through the layers of the city as information. The data can come from citizens, devices and assets that may be mobile and located throughout the city. Citizens can use their mobile phones and smart watches to report data to the city authority. In Fig. 1 layer 4, there are connected vehicles that can report traffic data to the traffic authority to help schedule lights to optimize the flow of traffic. There are a number of smart trees that have moisture sensors at the roots to ensure that they are watered at the correct interval. There are a number of connected CCTV cameras located throughout the city as a deterrent for crime and also to be used as evidence for criminal behaviour. There are a number of 5G cell towers located throughout the city that provide fast and low latency access to the internet. A connected fire device has just sent an alert to the fire brigade from one of the six tower buildings in the city after detecting smoke in one of the apartments. Wind sensors have also been deployed near the monument offshore as well as on the boats to collect data for the possible design of an offshore wind farm.

3.6. Virtual layer/digital twin

The virtual layer/digital twin builds on the data that is produced from the digital layer/smart city. There is a connection between the virtual layer and digital layer as shown by the arrows in Fig. 1. Data is sent from the digital layer about the mobility, infrastructure, buildings and terrain in the city. This data is used to conduct simulations in the virtual layer, which can then be passed back as information through the layers of the city. For example, in Fig. 1 wind data is being collected offshore at the digital layer. This data is then used to conduct simulations on the viability of using offshore wind turbines to meet the renewable energy targets for the city. A highly realistic digital twin of the turbines can be developed using the wind data collected in the digital layer to influence the size and placement of the turbines. This digital twin can then also be used to evaluate the visual impact of the turbine placement as citizens may not want the turbines placed close to the offshore monument. Additional tracking information from the offshore boats can also be used to help place the turbines in an area that will not affect offshore traffic. In this case we are only using the relevant components from each of the layers. For example, we do not need the city terrain information, city buildings, urban traffic mobility model or 5G telecommunications model to run this simulation. We only use the relevant wind, offshore boat and feedback data from the citizens to decide on the size and placement of the offshore wind turbines.

The digital twin can also be used to aid with the construction of buildings in the city. In the digital twin layer in Fig. 1 we can see that two new large buildings are being proposed: a circular skyscraper and the building with a spire on top. Using the sensing data collected in the digital layer, simulations can be created in the virtual layer to see how these buildings will affect the sunlight in the city e.g., would they block the sun from existing parks. Wind and seismic data collected in the digital layer can also be used in the design of the new buildings. Once a digital twin of the new buildings has been created they can be tested against the known challenges of the city, such as high winds or being near an earthquake fault line. Once the buildings have attained the appropriate building safety certificate they can be added to an online digital twin.

The online digital twin allows citizens to easily walk around and give feedback on new urban policy and planning decisions. Citizens can enter forms to give feedback on newly proposed buildings or green spaces, such as parks in the city. This allows the digital twin to generate additional smart city data that can be used to create information through experimentation, which is fed back through the layers of the smart city. For example, in the green space simulation in Section 5, citizens could propose new items that they wanted to be included in a new park, which led to the inclusion of a children's play pen option, which was not one of the original proposed options. Fig. 3 shows the online digital twin interaction diagram. We can see how the model being deployed online over the internet allows for easy citizen feedback. This feedback can then be send to the relevant group, such as the researchers who developed the urban mobility model or the city council, who provide the urban IoT data. The city council can then use this data to make informed decisions about urban planning and policy. The main stakeholders for each of the components of the online digital twin are also shown with the blue box indicating the main technologies used.

4. Experimental setup

4.1. Simulation software

Unity3D Software (Unity), version 2019.2.10f1 Personal, was used to load the digital twin, which is a 3D FBX model that contains the first

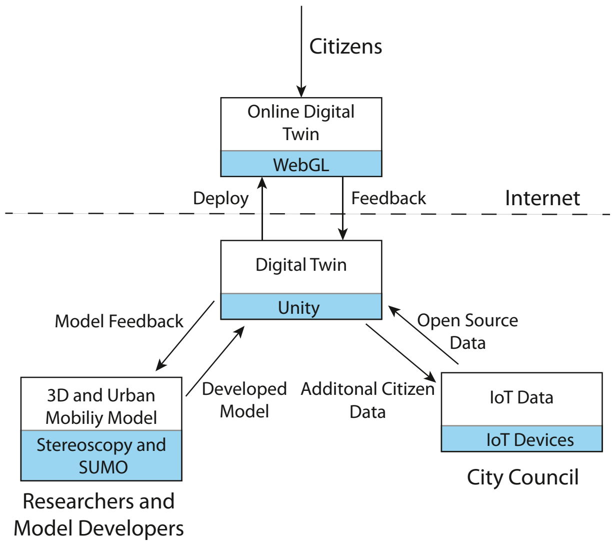


Fig. 3. Online digital twin interaction diagram.

three layers of terrain, buildings and infrastructure. Pedestrian mobility models were implemented in Unity to allow for crowd simulations, with different agents types, including adult and elderly using data from an experimental study (Oxley et al., 2005). Smart city data is taken from the Dublinked[7] site to make the simulations as accurate as possible. The twining with real public data from an open portal allows the model to evolve over time and allows for multidisciplinary modelling of the city (Castelli et al., 2019). A city is always evolving over time with new buildings and data available from the city about crowds in the city or flooding information. This new data creates a feedback loop allowing the digital twin to test the models and predictions on unseen data.

4.2. Skyline simulation

A version of the model has also been made available online.[2] A 3D model allows for the easy removal and addition of newly proposed buildings. This can be useful for conducting simulations to evaluate the response to new buildings being introduced in the city and how they would affect the skyline. Any proposed building plans can easily be added to the digital twin using the BIM model. This model would then allow citizens and public officials to walk around the digital twin and see the effect that the new building would have on the skyline from a number of different locations. The sunlight information from the smart city combined with the BIM file of the new building could be combined to simulate the effect that a large building would have on the sunlight access of nearby parks or public spaces.

Building works are long term projects and can take years to complete. This can lead to a large difference between the current view of the city and what the city will look like when all the current building projects are finished. In our simulation, we show a current view of the model with all the current buildings finished compared to the current view in the street to highlight this point. We also add some additional BIM models as assets to our digital twin to show how the skyline would be affected by new buildings. In the digital twin model that is deployed online, citizens can be presented with a form that they can use to give feedback on the newly proposed building. The form asks for the citizens name and email for verification, then the user can vote on whether or not they approve of the new building. Once the user has voted on whether or not they approve of the new building they can leave additional feedback in a text box explaining the reasons why they approve or disapprove of the new building.

4.3. Green space simulation

Green space, such as parks and recreational spaces are hugely important in smart cities for promoting healthy living and wellbeing (Anguluri & Narayanan, 2017; Lee et al., 2015). The digital twin model allows for development of these green spaces in suitable areas of the city. Data from the smart city, such as air pollution, noise pollution, pedestrian traffic flow and amount of direct sunlight can be used to influence urban planning decisions of where to place these green spaces in the city.

If the park or green space gets urban authority approval then the smart city can be used to track the number of people that visit the new green space. Different facilities in the park, such as extra benches or new flowers can be modelled using the digital twin, while also presenting a selection of options for users to choose or propose new suggestions. The success of this additional equipment can also be tracked through the use of sensors in the smart city. In our simulations we add additional tree locations throughout the city and create a new park. Citizens can leave feedback about what additional equipment they would like to see in the new park by selecting from the following options: more benches, more summer flowers, park gym equipment or other. By selecting the ‘other’ option the citizen can leave a suggestion that is not one of the considered options, which may provide additional information of the local citizens needs for urban planners.

4.4. User tagging simulation

The initial form-based skyline and green space simulations can be extended to allow citizens to walk around the model more freely and tag objects within it. With an accurate digital twin available, citizens would be able to tag real life problems in the model and then have the information sent to the relevant government department. This message would have the exact location of the issue as seen in the model.

The digital twin can also be used in disaster scenarios to easily show citizens in the city the areas will be most affected by flooding and the roads that will become inaccessible. Citizens can also tag their current location in the digital twin and whether or not they are in need of assistance. This user tagging would enhance the data generated by the smart city and would allow for more detailed simulations when using the digital twin in future as the locations of where most citizens needed assistance would be captured. The actual level that the water rose based on the amount of rain would also then be fed back into the digital twin to ensure that the model has an accurate model for predicting the water level based on rainfall.

4.5. Flooding simulation

Accurate flooding simulations require the detailed 3D terrain and building information provided in a digital twin. Unity allows the loading of a 3D digital twin, which contains accurate street elevation information. This allows the water level to be dynamically altered, showing the areas that would first be affected by a river flooding its banks or heavy rain. These simulations can be useful for urban authorities in flood planing by deciding where to deploy sandbags and what areas of the city to evacuate first.

Data from the smart city about rainfall amount and river levels can be fed to the digital twin to create a timeline of when flooding could occur. This information can then be passed from the digital twin back to the smart city to alert citizens of the timeline for a possible flood. The historical data collected from the smart city can then be used to create longer term flood prevention mechanisms if flooding is identified as a problem for the city. This could be for large scale projects, such as introducing water storage areas or diverting rivers. Previous flooding simulation approaches have integrated propitiatory flooding models, such as Mike Flood and have focused on the economic cost caused by

[7] https://data.smartdublin.ie/.

floods (Pyatkova et al., 2019). Our approach is focused on urban mobility and identifying the areas that are susceptible to flooding in the city.

In this flooding simulation we raise the water level in the River Liffey in Dublin to identify the surrounding areas that would be most affected by the river flooding its banks. This simulation is able to identify roads and walkways that would become inaccessible to vehicles and pedestrians in a flood, which would alter the movement patterns in the city. This is especially important for one way roads where vehicles may become stuck and not be able to turn around. Our initial model is simplistic, only taking into account rainfall and river levels, but it can be extended to include additional information about currents, materials in the river beds, sewage and drainage systems. Our model is validation using data from the office of public works, which has historical data on past floods in Ireland and gives low, medium and high probability ratings to a current area being flooded.

4.6. Crowd simulation

The crowd simulation can be carried out anywhere in the model, but was mostly focused around an intersection just north of the Samuel Beckett bridge. Spawn locations were placed at entry points to the maps, as a general collection at the four corners of the main intersection and at the exits of the 3Arena. These sets of spawn locations are the children of empty objects that describe the set and any of the sets can be used for a flock to set the spawn locations and destinations. The average waiting time and the average distance travelled was then compared between the agent types. The two agent types elderly and adult, were spawned at different ratios: 0–100, 25–75, and 50–50 splits. The Elderly agents have a smaller maximum speed range, step height and wider radius so that they would not make as sharp turns, which is based on an experimental evaluation (Oxley et al., 2005). Their average waiting times and distance travelled were then compared.

A flocking algorithm was developed to control pedestrian movement. This is done by assigning behaviours to the pedestrians, which will be referred to as agents. These behaviours determine how the agent will move when interacting with its environment and other agents. The core of this algorithm contains three scripts, FlockBehaviour, FlockAgent, and Flock. The first, FlockBehaviour is a scriptable object, which all behaviour scripts inherit from. Each behaviour creates a movement vector that are summed to find the agents next move. The second and third are both Monobehaviours that govern the properties of the flock. FlockAgent controls individual properties and stores data that is unique to the individual agent, while Flock controls anything that is universal to the flock. The three basic behaviours needed are cohesion, alignment and avoidance. These ensure that the flock of agents move together, in the same direction, and that the agents do not overlap with each other. Other behaviours have been added to make a more realistic crowd simulation or to incite reactions to any introduced stimuli. The flocking algorithm is made publicly available.[8] The crowd simulation is validated using public data from the pedestrian footfall index in Dublin city centre provided by Dublin's open data portal[7]. The model can evaluate the accuracy of the predictions using unseen data, which it can then use to update the model creating a continuous learning cycle.

5. Results

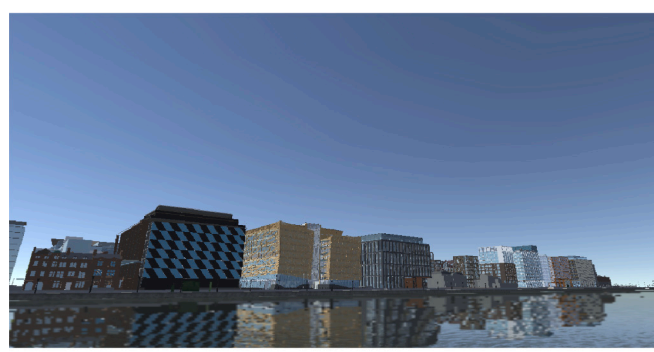
5.1. Skyline simulation

A 3D model provides a low barrier to entry for citizens to become engaged in city planning decisions as no detailed technical knowledge is needed. The buildings are simulated in 3D and citizens can report if there are any problem. Fig. 4 shows a comparison between a current view of the Docklands available on Google Maps and the current simulated model. We can see that there is a large difference between the current view in Fig. 4a and the model view in Fig. 4b, with many buildings still under construction. The digital twin gives citizens easy

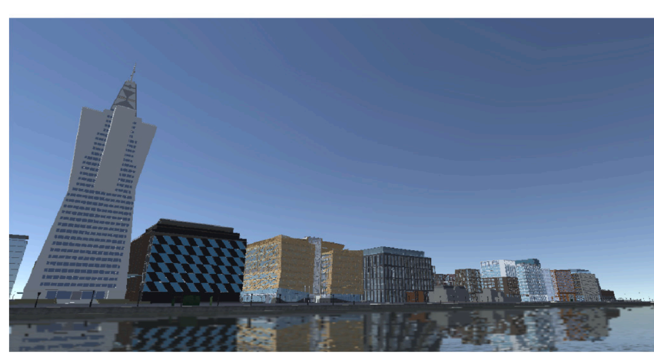
(a) Current Street View

(b) Current Digital Twin

Fig. 4. Approved building works.



(a) Current Digital Twin



(b) Proposed Buiding Digital Twin

Fig. 5. Planned buildings.

[8] https://www.scss.tcd.ie/~whiteg5.

access to what their city will look like in the future as these buildings can take years to complete.

Fig. 5 shows a proposed building addition, based on the Transamerica Pyramid that would change the skyline in Dublin. Fig. 5a shows the current model of the city and Fig. 5b shows the proposed building plan. This provides easy access to city officials as well as the public to walk around the city and identify some of the problems that a large building like this may have in the city, such blocking sunlight or cell towers. This allows any complains to be heard before the building has begun construction.

Fig. 6 is the feedback that has been collected from 30 citizens in the area though an online form. The citizens were asked whether they approve of the new building proposed in Fig. 5b. From the data collected 78% of citizens approved of the new building, while 22% disapproved. Citizens were then able to leave comments on why they chose to approve or disapprove the design of the new building. The comments for people who disapproved of the building were that "the design didn't fit in with Dublin's architecture" and that "it is too tall and sticks out compared to surrounding buildings". This can provide useful insight to urban planners and policy makers to update the design of the building.

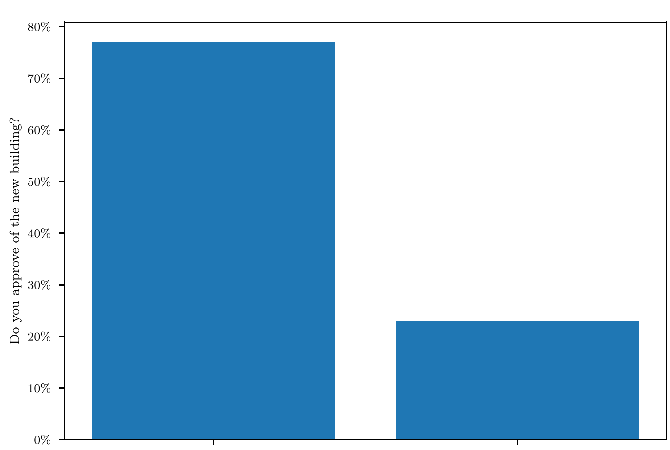


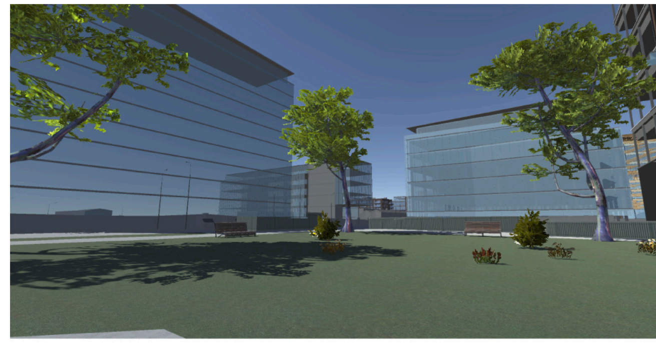
Fig. 6. Skyline simulation feedback.

5.2. Green space simulation

The Digital Twin concept can also be used for the creation of green space throughout the city, this can be by the creation of new park spaces in the city or planting additional trees. Cities can benefit hugely from the creation of green spaces with new parks in between buildings. Fig. 7a shows a simple demonstration of a park that has been created in the city centre as a place for residents and workers to relax. The amount of citizens using the park can be tracked using sensors in the smart city. As the digital twin is available online users can give feedback by interacting with the model and leaving suggestions. This can be the placement of new benches, trees, plants or outdoor park fitness equipment. The sensors from the smart city can be used to track engagement with the additional equipment.

Fig. 7b shows a smaller green space created in the city by planting some additional trees. Simulations using data from the smart city can be used to ensure that the trees have access to a suitable amount of sunlight, temperature and water throughout the year. Citizens in the local area could also give feedback by selecting from a short-list of trees chosen to be suitable in this area.

Fig. 8 shows the results of the feedback on additional items that should be included in the new park. Three of the options: more benches, more summer flowers and park gym equipment were proposed in the form. The other extruded option for a children's play pen was suggested by a user in the form and then added as an option, which become the second most popular option. This encourages citizen engagement as they can see that the options are being changed based on their feedback. The most popular option was for park gym equipment, this could be due to the location of the park in a financial district where employees would like the option of getting some free exercise outdoors.



(a) Park Creation

(b) Additonal Tree Placement

Fig. 7. Green space.

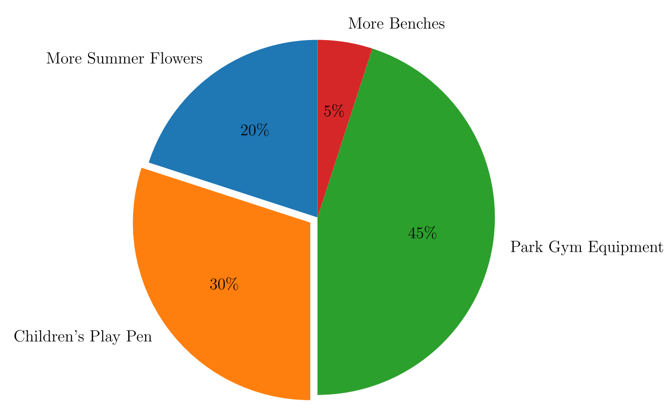


Fig. 8. Green space simulation feedback.

5.3. User tagging simulation

The availability of a 3D model allows users to interact with and report objects in the scene. Fig. 9 shows a user interacting with a street light in the 3D model. Interacting with the street light gives the user the option to report an issue such as the light not working or the light switching on while it is still bright outside. This report can then be sent to the city council to fix the problem, with a detailed report of the exact location and problem that has to be fixed. Citizens interact with a number of different objects in the environment reporting problems such as litter, antisocial behaviour, traffic congestion, graffiti and mistakes in the digital twin that need to be re-scanned. This allows for the easy

Fig. 9. User reporting problem.

generation of additional smart city data that can be used to identify the problems that are most often reported by citizens.

Fig. 10 shows the user tagging feedback that was collected in the simulation. We can see in the top left corner of the map there have been a series of user tags to report problems with litter in this area. This can then be reported to the Dublin litter wardens and environment health officers, with the specific location of where the problem is occurring. Preventative measures, such as increased CCTV or litter warden deployment can then be implemented in that area to tackle the problem. Some of the other areas where problems were tagged in the model can also be seen in the map. These were for problems, such as lights not working and potholes in the road. Both of these problems can also be forwarded to the relevant department with the exact location of the problem. The data can be stored long term to conduct a detailed analysis over time of how council resources are being deployed to different areas and what are the specific problems or locations that are often being tagged.

5.4. Flooding simulation

Digital Twins can also be very useful for emergency situation simulations as they allow for the simulation of events that happen very rarely. Fig. 11 shows the simulation of a flooding scenario in the Docklands. The simulations are able to show how a rise in water level from the River Liffey would spill into the surrounding streets. From Fig. 11a–f we can see how the increase in water level leads to more damage and how each area in the city centre would be damaged. This information could be used for the effective placement of sand bags and other flooding countermeasures to protect the areas most at risk.

This flooding information can also be used for effective urban evacuation. Urban authorities can make projections about how far the water will rise given the forecasted rain (Alvisi et al., 2006). This will allow them to identify the areas that are most at risk and begin evacuating people in those affected areas first. Urban authorities will also have time estimates to evacuate these people as they can forecast how long it will take for the water level to rise that amount. The flooding model can

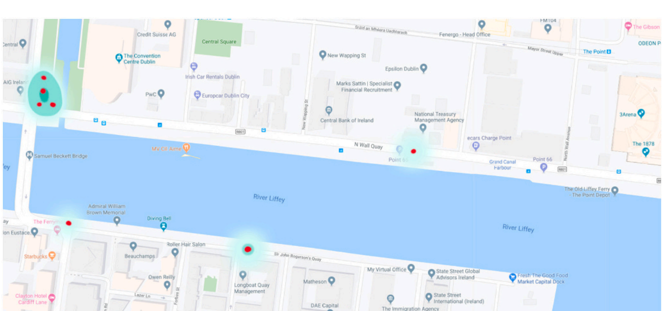
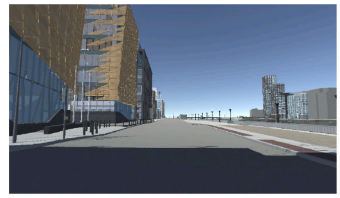
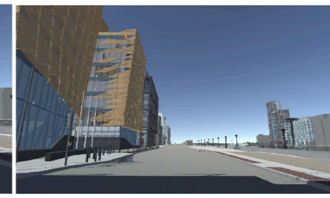


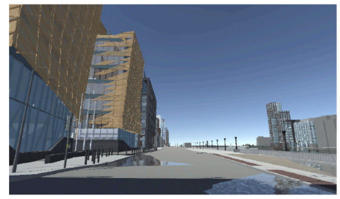
Fig. 10. User tagging feedback.



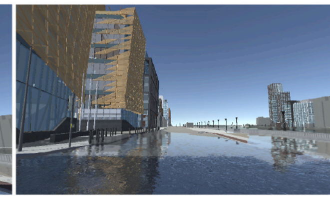
(a) Water Level = Raised 2m



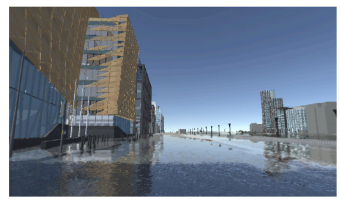
(b) Water Level = Raised 3.2m



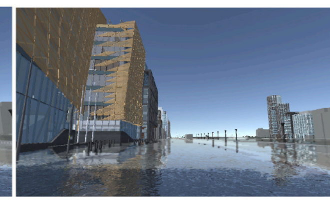
(c) Water Level = Raised 3.3m



(d) Water Level = Raised 3.5m



(e) Water Level = Raised 3.7m



(f) Water Level = Raised 4m

Fig. 11. Flooding simulation.

then be evaluated at times when flooding occurs. Additional complexity can be added to the model to include currents, materials in the river bed, sewage and drainage systems. The goal is not to create a perfect model first time, but to create an open model that can be incrementally improved with additional data and combined with other digital twin simulations, such as crowd simulations.

5.5. Crowd simulation

The crowd simulations create two types of pedestrians in the Unity model: a standard Adult agent and an Elderly agent. The average wait times, distance travelled and time in simulation were compared between the two types. Fig. 12 shows the average wait time and Fig. 13 shows the average distance. The average wait time for the adults and elderly in Fig. 12 does not vary much as the percentage of elderly in the simulation increases. However, there is a noticeable difference between the two agent types with the elderly agents having a much longer waiting time.

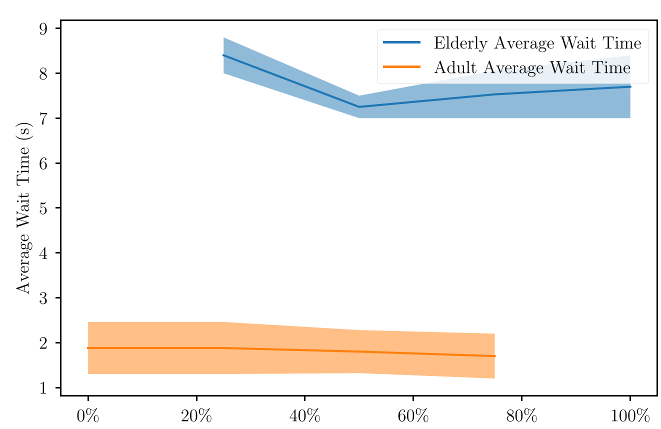


Fig. 12. Average wait time of the agents vs. the percentage of the flock that is of the Elderly type.

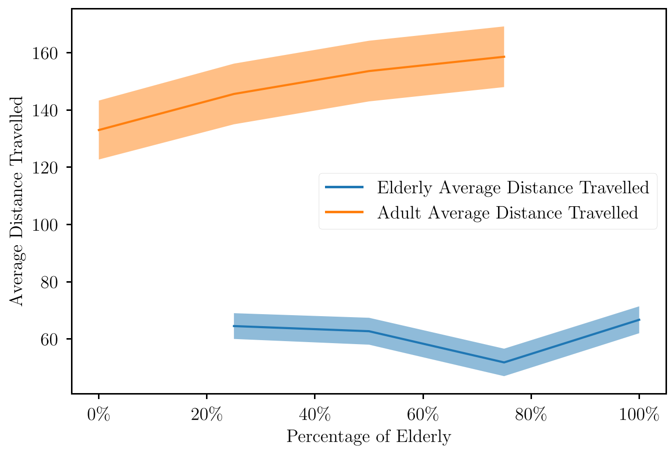


Fig. 13. Average distance travelled by the agents vs. the percentage of the flock that is of the Elderly type.

This is due to the elderly agents having less mobility and movement speed, which means that they can take longer to move around obstacles and go through traffic lights. Further experimentation can evaluate how individual street furniture (e.g., bins, lights, footpath width etc.,) effects the waiting time of pedestrian types as they move through the city. The results from these simulations can then be used to inform urban planning and policy.

Fig. 13 shows the average distance that is travelled by the agent types. The elderly agents distance travelled remains quite constant. However, the adult distance travelled increases as the percentage of elderly agents in the simulation increases. This indicates that the adult agents can use their increased speed to move around any elderly agents in the simulation or obstacles. This keeps their average waiting time low as shown in Fig. 12, even though the distance they travel increases with the percentage of elderly people.

6. Limitations of current digital twin

In this section we identify some of the limitations of the current Digital Twin through the layers of the model outlined in Fig. 1. This is the first version of the model to be released and these limitations can be addressed in future versions.

6.1. Buildings

The Docklands model includes a large area of Dublin, some of the modern buildings along the waterfront are captured in great detail. However, there are some areas in the model, especially of older buildings and open spaces, such as the Bus Depot in Fig. 14 that are represented by grey boxes. Although the function of the grey box cannot be determined from the model it does not affect the functionality of the citizen feedback or crowd simulations.

(a) Physical Bus Depot (b) Virtual Bus Depot

Fig. 14. Physical and virtual bus depot comparison.

6.2. Infrastructure

The rail bridge near Samuel Beckett bridge is shown as seen in the physical world and in the digital twin in Fig. 15. Fig. 15a and Fig. 15c show the comparison of the physical and virtual left side of the bridge. The virtual representation of the pedestrian path is narrower than the physical model. The bridge also has legs sticking out that cover the pedestrian footpath area in the model. Changes to the size of the footpath and the position of the bridge were implemented in Unity to make the simulations more realistic.

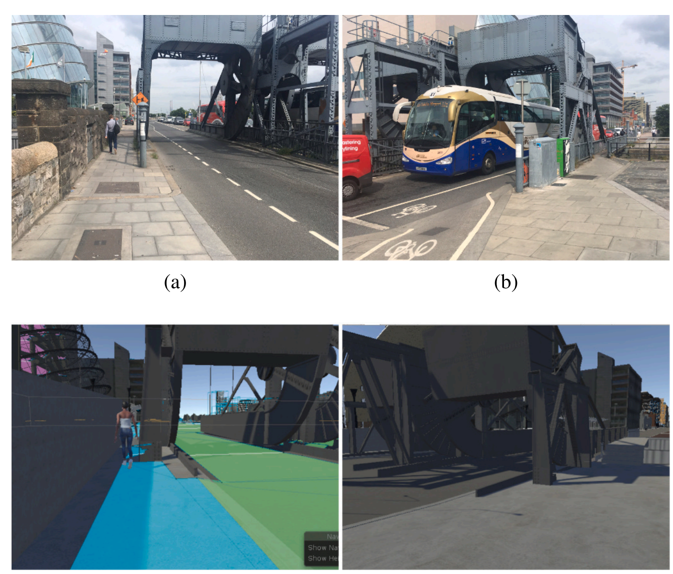
Fig. 15b shows the right side of the bridge in the physical world and Fig. 15d shows how this is represented in the digital twin. The digital twin is missing the small bridge as seen in Fig. 15b to allow pedestrian access on this side of the bridge. A small bridge structure as shown in Fig. 15d is created in Unity to allow for more accurate pedestrian simulations.

6.3. Mobility

There are some urban mobility systems that are not included in the model. For example, Dublin has a light rail system called Luas that is not included in the model. The addition of this light rail system would allow for more detailed urban mobility simulations and the comparison between a range of urban mobility systems. There is also a lack of bus stops and road markings in the model, but this information can be added to the model using OpenStreetMap.

6.4. Smart city

Data produced from the smart city is what drives the accurate simulations in the digital twin. Dublin makes a lot of data available through the Dublinked[9] open data source. This provides a number of data sources about population, transportation and infrastructure as well as information about the environment and energy. However, there is a lack of fine grain data, which is often aggregated. This can lead to having to interpolate datasets, which leads to less accurate simulations.



(a) (b) (c) (d)

Fig. 15. Rail bridge that has pedestrian pathways to either side of it, but cannot be passed in the 3D model.

[9] https://data.smartdublin.ie/.

7. Conclusion and future work

The results section has illustrated a range of simulations that can be carried out by using a digital twin of a smart city. The results from these simulations can feed back through the layers of the digital twin model, as shown in Fig. 1 to advise on real changes in a smart city. The digital twin can be used to engage citizens and get a lot of valuable feedback on key urban planning and policy decisions. The results of skyline and green space planning simulations have shown how user feedback and suggestions can be collected to provide additional data to inform urban planning and policy decisions to allow for additional changes before a final decision is made. In the green space planning simulation options can be left open to allow citizens to propose their own ideas, such as a children's play pen in the park. These initial form-based methods can be extended to a tagging model as shown in the user tagging simulation. This allows citizens to interact with all the objects in the digital twin and tag problems or suggestions. These problems or suggestions can then be sent to the relevant government department with the exact location of the problem.

A digital twin can also be used for a range of other urban planning decisions and policy. As the model is 3D, it allows for the simulation of rare events that require 3D data, such as flooding in the city. This can then inform the city's policy of what areas of the city to evacuate first and where to best place sandbags. The crowd simulation in Section 5.5 has shown how multiple agents types, such as adults and elderly can be created in Unity using mobility data from previous experimental studies (Oxley et al., 2005). These simulations can be extended to evaluate future urban planning decisions in a smart city such as the impact that a change in gradient of a footpath or adding additional street furniture will have on different pedestrians, such as adults and elderly. In future work, we plan to extend the public data that we use for the simulations with data from additional IoT services in the surrounding area. These services may be provided by the city council or from private citizens or companies in the area. The increased amount of data would allow for more realistic simulations with real time information about crowds, noise pollution and traffic in the area. This digital twin model with mobility data can be adapted to multiple other scenarios that were not investigated in this paper. In future work, we plan to evaluate a concert simulation that would see an influx of pedestrian and vehicle traffic attempting to reach the Three Arena in Dublin (capacity 13,000). Simulations could investigate the placement of fire evacuation points as well as the effect that increasing the capacity of the stadium would have on the traffic and fire evacuation policy.

CRediT authorship contribution statement

Gary: Conceptualisation, Writing – Original Draft, Software, Visualisation.

Anna: Software, Writing – Original Draft.

Lara: Writing – Review & Editing.

Siobhán: Writing – Review & Editing, Funding Acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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