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HEALTH SENSITIVE DECISION-MAKING FOR INTEGRATING ARTIFICIAL INTELLIGENCE AND LANDSCAPE ARCHITECTURE IN URBAN CITIES

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Highlights:

- to design the urban greenspace layout using Generative Adversarial Networks (GAN) by satisfying the functional needs, shape constraints, and architects' health promotion goals;
- maximize accessibility, usage, and safety by using reinforcement learning procedures to explore the space layout;
- to recommend the supervised AI techniques to determine the health-promoting choice for specific zones and ecosystem services of landscape architecture.

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Abstract. Urban landscape architecture design plays an essential role in public health because it is influenced by several factors such as social connection, safety, walkability and amenities access. Traditional planning techniques are time-consuming and often result in suboptimal or aesthetically incoherent layout decisions, which diminish the accessibility and safety of landscape design. The research issue is addressed by integrating artificial intelligence (AI) techniques in architectural design to improve the overall aesthetic design while handling health decisions. This study uses Generative Adversarial Networks (GAN) and Reinforcement Learning (RL) to satisfy the health objectives via landscape layouts. The GAN uses the generator and discriminator to design the landscape layout that covers inputs such as functional requirements, site dimension, zone restrictions and health design principles. The combination of generator and discriminator helps to maximize the outcomes in injury prevention, mental restoration and physical activities. The generated layouts are further explored using RL rewards regarding usage, safety, and access, ensuring the layout appearance and aesthetics are directly tailored to health. The incorporation of new technology into landscape architecture can offer evidence-based approaches for constructing salutogenic landscapes. The scalable computational technique enables faster scenario evaluation, providing information for informed planning policies. Then, the excellence of the landscape layout is evaluated using experimental results.

Keywords: urban landscape design, landscape management, Artificial Intelligence, Generative Adversarial Networks (GAN) and Reinforcement Learning (RL), health outcomes.

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1. Introduction

Urban green landscapes (Reyes-Riveros et al., 2021) significantly improve city residents' health and wellness through architecture. As urban regions experience increased population density, well-planned gardens, playgrounds, and other green spaces become crucial in providing city dwellers with access to nature, offering open spaces for physical activity and leisure, and serving as havens from the pressures of urban living (Jabbar et al., 2022). Studies have shown evident correlations between the availability of urban greenspace and enhanced physical health, achieved through heightened physical activity and relaxation. Additionally, effective landscape architecture offers mental health benefits (Allahyar & Kazemi, 2021), including reduced stress, anxiety, and sadness (Olszewska-Guizzo et al., 2023). Therefore, landscape architects must consider several elements such as safety, affordability, sustainability, diversity and social identity in their design, maximizing potential health benefits (Ou, 2021). Through attentive landscape architecture, urban greenspaces have the potential to improve the quality of life effectively.

Modeling virtual visitors in the RL simulation used an agent-based pedestrian mobility framework influenced by the Social Force Model and cellular automata-based crowd dynamics. Basic behavioral norms include preferred walking speeds, obstacle avoidance, attraction to facilities, and avoidance of poorly lit or lonely regions. This method is supported by urban planning pedestrian behavior research. Moving patterns were calibrated using public pedestrian datasets like UCY and ETH to ensure realistic route choices and crowd distributions in parks. Designers face several challenges when creating landscape architecture that effectively improves health in densely populated metropolitan contexts. Given limited space constraints, landscape architects must employ innovative techniques to create functional green areas and prevent the mere construction of small, ornamental parks. Sustaining accessibility (Bharmoria & Sharma, 2023), attractiveness, safety, and cleanliness in high-traffic public venues can be challenging (Wen et al., 2020). Therefore, landscape is essential to carefully analyze the ecological implications of decisions and the ability of plants to withstand harsh urban circumstances such as heat island effects and air pollution. Landscape architects (Wen et al., 2020) are responsible for identifying the best locations and sizes of green areas to maximize their accessibility to the most significant number of citizens while also considering cost-effectiveness. Programming public health initiatives also faces challenges in promoting physical activity and facilitating social interactions amid daily urban pressures that prevent the prioritization of well-being. Striking a balance between practicality and ambitious design complicates creating health-promoting settings. Latest AI and AIoT breakthroughs provide smart cities game-changing environmental performance and efficiency improvements. The research covers smarter eco-cities' cutting-edge use of AI and the IoT to improve environmental sustainability. To accomplish completeness, Bibri et al. (2024) adopts a unified evidence synthesis framework with aggregative, configurative, and narrative methods. ML can help solve urban spatial planning difficulties, leading to more ML papers across fields. This gap is addressed by Casali et al. (2022), who direct urban science and spatial data analysis researchers to the most utilized methodologies and unfilled research gaps. Scoping assessment of ML research that analyzed metropolitan regions using geospatial data. The view highlights key subjects, data sources, ML algorithms, and parameter selection strategies. Furthermore, identify the most significant ML themes and problems. Use the study to discover ML knowledge gaps in spatial data science and data specifications to drive future research.

Then, Artificial Intelligence (AI) (Pena et al., 2021) techniques are incorporated with the landscape architecture design to address issues such as improper landscape design, failure to meet the user requirements etc. The AI-generated design helps create innovative structures for irregular and small urban sites with specified constraints. The AI technique rapidly executes the functions, processes, and options that lead to the generation of several design solutions. During the analysis, spatial analytics AI explores geographic information to identify the optimal size and placements of urban greenspace connected via mobile networks (Casali et al., 2022). The AI techniques are applied in the crowd simulation model that analyzes human safety, traffic flow, availability, accessibility and human-centric metrics, effectively refining the landscape structure. Then, AI with environmental modelling is utilized to select the materials and landscape design to manage the urban ecology, island heat, stormwater runoff and mitigate the landscape design. Post-occupancy assessment AI can collect on-site sensor data and user feedback on security, usage rates, ease of transit, and other factors to help inform evidence-based modifications. Several AI techniques, such as Artificial Neural Networks (ANN) (El Alaoui & Rougui, 2024), Radial Basis Neural Networks (RBNN) (Arifuzzaman et al., 2020), etc., are utilized to examine the urban space to generate effective architecture. However, traditional architects lack the tools to intellectualize the layout fittings for health functions (Zhang, 2020). Then, the existing techniques face complexity while selecting dynamic elements, resources and navigations that create challenges while quantifying the health impacts. The research difficulties are overcome by introducing two AI approaches: Generative adversarial networks (GANs) (Wu et al., 2022) and Reinforcement Learning (RL) (Huang et al., 2020). The GAN approach enhances the architect's productivity and creativity while engaging the health spatial plans. In addition, the RL enables the data-driven and trial-error optimization procedure in health-tuned design that improves the landscape structure. Then, the main contribution of the work is listed as follows.

- To design the urban greenspace layout using Generative Adversarial Networks (GAN) by satisfying the functional needs, shape constraints, and architects' health promotion goals.
- Maximize accessibility, usage, and safety by using reinforcement learning procedures to explore the space layout.
- To recommend the supervised AI techniques to determine the health-promoting choice for specific zones and ecosystem services of landscape architecture.

2. Related works

This section discusses the previous researcher's works on artificial intelligence and landscape architecture in urban cities for making sensitive health decisions. The summary of the related works is presented in Table 1.

Creating health-promoting built environments in densely populated and complex metropolitan areas poses a highly complicated and multidimensional task. AI provides landscape architects the computational power to investigate and recognize the complex factors that influence public health, addressing them systematically. Geospatial analysis, Combined with Artificial intelligence, analyzes patterns of movement, environmental conditions, and societal requirements to locate peaceful green areas strategically. AI allows quantitative optimization, predictive spatial analysis, and human-centered design toolkits, making urban planning decisions more precise and data-driven. AI systems can evaluate complex, multidimensional datasets to find optimal configurations, predict design implications, and adjust solutions to user behavior and environmental constraints, unlike heuristic or subjective guesses. AI is a crucial platform for transforming cities into healthier environments for humans. It plays a vital role in enhancing

Table 1. The summary of the related works

Authors	Title	Methods utilized	Findings
Pala et al. (2020)	Utilizing deep learning techniques to uncover associations between urban environment and population health	Applying deep learning networks for analyzing the U-funded participatory urban living sustainable environment project in New York City	Examined the correlation between health outcomes and urban structure using satellite images effectively
Jahani and Saffariha (2020)	An environmental modeling technique is applied to predict aesthetic preference and mental repair in urban parks	This work explores aesthetic preferences and analyses urban parks' mental restoration values	The system's efficiency is compared with SVM, RBFNN and MLP networks. From the analysis, urban park landscapes are predicted to recover from mental stresses
Chen (2023)	An environmental landscape design and planning system that utilizes computer vision and deep learning techniques	Analyzing landscape design elements and plans using human-centred computing and deep neural networks	This process successfully analyzes environmental pollution, removes toxins in the air, and makes it easy to manage the environment healthily
Chen et al. (2022)	3D landscape design and optimization for digital cities using wavelet transform	Designing 3D landscape design in cities by using the wavelet transform-based denoising approach	Able to maintain the image texture information and attain faster convergence speed with minimum error
Mishra et al. (2020)	The creation of a tool to evaluate the environmental characteristics of urban blue areas	This study assesses blue-health environment evaluation tools to determine the environment's influences on health-promoting activities	Developed public health resources by examining urban space's quantitative and qualitative measurements
Jia (2022)	A neural network model is developed for urban landscape design, which is based on multi-target detection	To design the system using a neural network with an objective testing process to overcome the manual acquisition characteristics of urban landscapes	The system attains 88% accuracy while detecting multi-objects and 0.57 s and 46 s for landscape generations
He (2022)	A neural network model is developed for urban landscape design based on multi-target detection	Analyzing China's urban city wetland park using building information model	This method ensures the effective landscape index fluctuates (2250 m)
Jahani and Rayegani (2020)	Assessing the visual quality of forest landscapes using artificial intelligence approaches to aid decision-making	Introduced AI technique with fuzzy decision system to analyze the forest visual quality for addressing the stochastic problems	The AI fuzzy set attains the highest test value while exploring the forest's high-quality satellite images
Silva et al. (2018)	Urban planning and decision-making for smart cities are enhanced by the utilization of real-time data processing facilitated by big data analytics	Integrating data filtering and normalization big data techniques to design, plan and maintain smart cities	The system attains applicability and reliability while developing the urban landscape architecture
Yu et al. (2023)	Utilizing the LSTM model, this study examines the optimization of urban green space facilities in China by applying artificial intelligence	This study intends to optimize urban road green belts to protect public health using long-term memory networks	This study attains 1.75 root mean square error, 1.12 mean absolute error, and 6.06 mean absolute percentage error
Senem et al. (2023)	Applying deep learning techniques to create realistic front and backyards in landscape architecture	This work uses Generative Adversarial Networks to optimize backyard and front layouts using different quantitative and qualitative attributes	This study analyzes the relationship between the AI and the urban city landscape architecture

the preventive capabilities of well-designed landscapes. By utilizing machine learning to process complex data sets, it is possible to establish sustainable urban communities in the present, which will cover the way for their development in the future. However, the existing systems consume high complexity due to the unavailability of data, which reduces the efficiency of the landscape architecture design. The research difficulties are addressed using AI techniques such as GAN and RL to improve the landscape architecture design.

Applying artificial intelligence to health-sensitive urban landscape design requires public confidence in AI, smart city environmental management, and societal awareness, according to recent study. In their study, Moravec et al. (2024) discovered that people's knowledge of AI is often lacking, even though it's becoming more common in everyday life. This highlights the importance of improving AI literacy and transparency in order to encourage society involvement and responsible use of AI.

Reviewing the literature on smart cities, Szpilko et al. (2023) emphasizes the revolutionary significance of AI in areas such as energy efficiency, pollution control, environmental monitoring, and transportation, all of which contribute to better urban ecosystems. The necessity for interpretable and sympathetic AI is further highlighted by Pelau et al. (2024), who show that individuals' trust and emotional reaction greatly impact their willingness to provide information with AI-driven systems. Ethical and successful design of AI-mediated health-focused urban landscapes requires integration of three dimensions—public knowledge, environmental functioning, and emotional trust.

3. Designing the urban space layout using Generative Adversarial Networks (GAN)

For developing efficient urban landscape plans, it is necessary to strike a balance between creative thinking and practical limitations. The efficacy of this procedure can be augmented by employing a GAN methodology. Initially, the landscape architect establishes the fundamental criteria, including the site's size, necessary features such as play areas and seating, the anticipated level of utilization, and the intended health goals, such as promoting social interaction and facilitating physical exercise. The details are inputted into the GAN algorithm, which comprises two adversarial neural networks. The generator network generates many potential greenspace configurations that comply with the specified spatial limits and criteria. Simultaneously, the discriminator network assesses each arrangement, evaluating its effectiveness in meeting the specified functions and health objectives. The feedback from the discriminator serves as a learning signal, allowing the generator to enhance its adherence in subsequent layout iterations. The latest prototypes aim to achieve greater levels of inventiveness while yet maintaining practicality. In the end, the generator network reaches a level of development where it consistently produces diverse designs that fulfil the given constraints. The adversarial training process between the two networks alters the distribution of computer-generated possibilities to align more closely with the priorities of human landscapes, achieving a harmonious blend of creativity and intentional design. Then, the structure of the GAN-based urban space landscape is illustrated in Figure 1.

Figure 1 illustrates the structure of GAN-based landscape architecture design. The urban site has been continuously examined according to site dimension, zoning restrictions, functional requirements, landscape elements, health design principles and style preference. The gathered inputs are fed into the GAN to create a compelling landscape layout and design plan. The method integrates spatial, functional, and health-oriented design objectives to develop ideal urban greenspace layouts using generative AI. The model involves preparing the site, encoding the data, interacting with GAN components, and synthesising the layout.

During the analysis, GAN uses three components: generated network, discriminator network, and adversarial training. These components help to create the design depending on the input, allowing us to make health decisions successfully. Urban landscape plans annotated with data from OpenStreetMap (OSM), architectural design repositories, and city planning databases make up the GAN's training dataset. Additional metadata on accessibility, utilization rates, and health outcomes supplement the semantic segmentation of these designs into named categories (such as green space, pedestrian walkways, sitting places, and water features). Weighted loss components punish poor element placement, misaligned zoning functions, and inadequate health-supporting characteristics; these constraints are used to impose input requirements during training and inference. Masking and conditional filtering, meanwhile, impose stringent limitations; for instance, zoning restriction maps invalidate layout sections outside of authorized construction zones. This two-pronged approach guarantees that GAN-generated landscapes are realistic in appearance, sound structurally, and designed to promote urban health in the best possible way.

GAN training instability issues including mode collapse and gradient vanishing were solved by the WGAN-GP approach. Using the Wasserstein distance instead of GAN loss provides more consistent and meaningful gradient updates during training. A gradient penalty was applied to maintain Lipschitz continuity in the discriminator (or critic) by measuring and regularizing the gradient norm

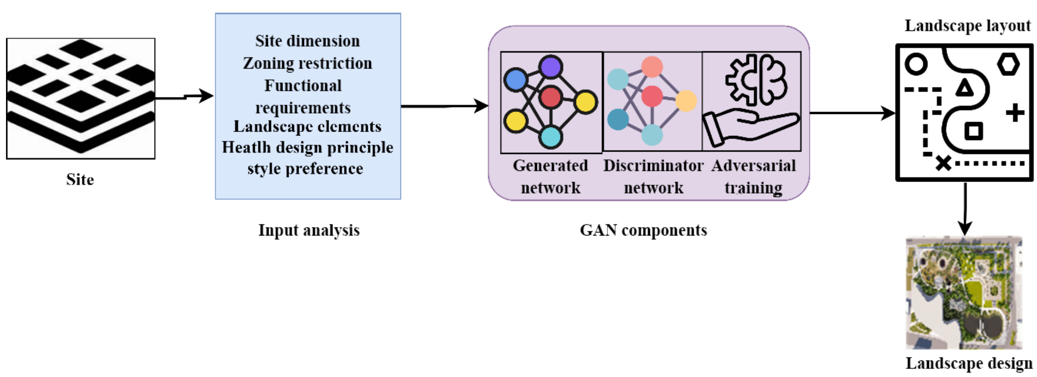

Figure 1. Structure of GAN-based urban space landscape architecture

between real and generated samples. This made convergence smoother and less oscillatory. Combine adaptive learning rate schedules and spectral normalization to stabilize training. These methods improved the GAN's reliability and robustness in developing valid and diverse landscape layouts.

A detailed description of each phase is explained below.

3.1. Input analysis

For generating highly efficient and contextually appropriate landscape architecture, it is necessary to have a substantial amount of fundamental data encoded to guide the GAN algorithm. The generator utilizes precise three-dimensional site contours from survey scans and architectural outlines to establish real-world spatial limitations. A computerized model of the city's layout, including three-dimensional contours and zoning maps created from geographic information system (GIS) or survey data, is the first piece of input. Site measurements, zoning regulations (e.g., buildable zones, setback lines), functional needs (e.g., seating areas, pedestrian paths, vegetation zones), health design principles (e.g., for safety, mental restoration, social interaction), and aesthetic preferences based on historical architectural patterns are all examples of inputs.

Structured tensors are used to encode each of these features:

(1) Spatial constraints: Geometric restrictions are transformed into grid maps or three-dimensional models based on voxels.
(2) Zoning rules and functional requirements: Layers of multi-channel zoning regulations and functional requirements are one-hot encoded, with each channel indicating the priority or permissibility of a particular function in a specific grid point.
(3) Style preferences: Using an autoencoder trained on historical photographs of architect-designed landscapes, style preferences are recovered as latent feature vectors. This allows stylistic priors to impact production.
(4) Heath metrics: Incorporating health measurements as a weighted vector based on rewards gives certain layout qualities (such open visibility for safety or clustered green zones for relaxation) more priority.

Supplementary zoning boundaries select the allowable activities, buildings, and layout for specific regions as tensor layers that filter out unrealistic proposals. Functional needs are translated into numerical values to provide accessibility by determining use flow rates and visitor capacity restrictions. A comprehensive collection of 3D-modeled components for the built environment, such as benches, pavilions, plants, paths, lighting, and more, provides modular parts for organizing space. These items are encoded with descriptive information tags. Public health research guides the exact landscape features, lane curvatures, and amenities that might have targeted wellness benefits, such as providing mental relaxation, promoting social connections, or encouraging physical activity. These prioritize health optimization as weighted priorities. In addition, references to an architect's previous designs provide insight into their geometric preferences and material selection, which may be used to match with generative design principles. The GAN fabrication engine utilizes specific site context, rules, functional requirements, component libraries, and wellness objectives to create urban landscapes detailed to local conditions and promote overall well-being.

3.2. GAN architecture

The collected site inputs are fed into the Generative Adversarial Networks (GAN), which can automatically process the multi-domain input data in the adversarial process, generating optimized landscape designs. Then, the structure of GAN-based urban space design analysis is illustrated in Figure 2.

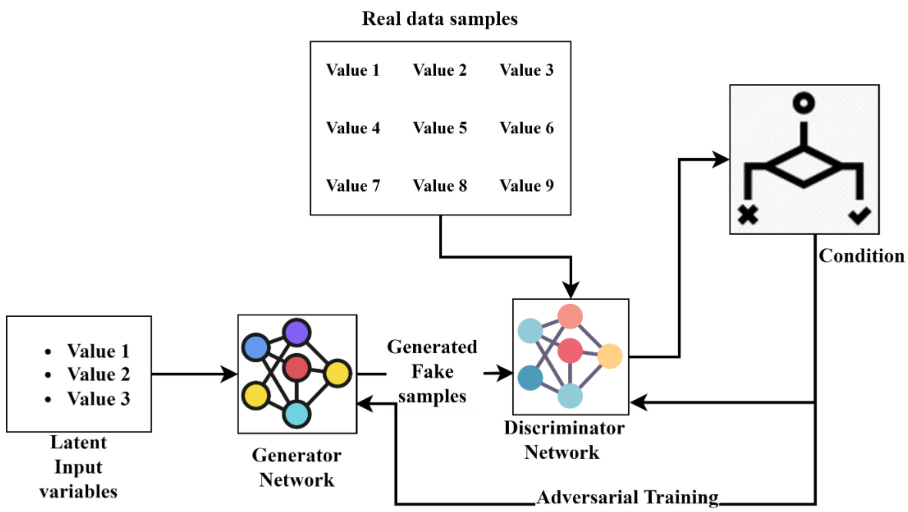

Figure 2. Working process of GAN-based layout design

3.3. Generator network

The inputs are applied to the generator network G that encodes the input zoning rules, spatial constraints, health guidance priorities, functional requirements and architecture style parameters into z latent vector. The site dimension details are pixelated and converted into 2D or voxelized 3D spatial coordinates maps. The conversion process generates the non-traversable or traversable zones. Functional traffic capacity restrictions, use timestamps, and adjacency priority quantify the relational significance between program components. Zoning allowances are colour-coded grids that display authorized applicable designations for each geographically placed pixel. The health principles and guidelines are represented numerically, such as ratings for social interactivities, biodiversity benefits, and water features. Entries in the 3D landscape component collection are represented as arrays containing information about their size, material qualities, and positional amenities stored as meta-tags. The architectural style is determined by evaluating geometric patterns and material palettes in the portfolio pieces and then creating histograms to represent the distributions. The different format constraints and desired data are combined into concatenated input vectors that are then used as input for the generator network. The latent vector z compresses the many alternatives into a concise summary, guiding successive iterations of the generative model to meet al. given planning requirements concurrently. The generator decodes the latent vector z to develop the landscape layouts (Lgenerator).

The proposed model utilizes a cGAN architecture to train its generator and discriminator networks, incorporating input constraints such as zoning rules, spatial dimensions, health design objectives, and stylistic preferences as conditional variables. A deep U-Net structure is used to build the generator so that site-specific information (such as zoning maps, functional annotations, and terrain elevation) may be encoded and decoded efficiently. To generate semantically coherent landscape layouts, these structured inputs are combined with the latent vector z, which is sampled from a Gaussian distribution. To determine if the produced layout is realistic and compliant, the discriminator—a multi-scale convolutional neural network—combinates visual fidelity with spatial-functional correctness. To ensure that the adversarial training process produces plausible and policy-compliant outputs, a composite loss function is used. This function combines the basic GAN loss with health-centric priority (Lhealth), spatial constraint penalties (Llayout), and the normal GAN loss.

3.4. Discriminator network and adversarial training

Simultaneously, discriminator D evaluates the produced layouts by comparing them to the encoded inputs regarding practical location appropriateness, zoning compliance, satisfying program criteria, embodiment of salutogenic rules, and compatibility with stylistic requirements. During the generator process, it reduces the log-likelihood value, indicating that discriminator performance is confirmed. Then, the likelihood loss function is computed using Equation (1):

$$J_G = \frac{1}{m}\sum_{i=1}^{m}\log D\left(G\left(z_i\right)\right). \tag{1}$$

In Equation (1), J_G is denoted by how effectively *G* fools the *D* and the log probability of the *D* being correct for *G* samples. The *G* intention is to reduce the loss value that maximizes the product samples, which *D* classifies as accurate. The loss value is estimated in the discriminator component that minimizes the negative log-likelihood of exactly classified both actual and produced samples. The discriminator component loss value is calculated using Equation (2):

$$J_D = -\frac{1}{m}\sum_{i=1}^{m}\log D\left(x_i\right) - \frac{1}{m}\sum_{i=1}^{m}\log\left(1 - D\left(G\left(z_i\right)\right)\right). \tag{2}$$

In Equation (2), J_D evaluates the discriminator's capacity to differentiate between generated and actual samples. The log probability of the discriminator correctly classifying actual data is shown as $\log D\left(x_i\right)$. The probability that the discriminator would accurately classify produced samples as duplicates is denoted by $\log(1 - D\left(G\left(z_i\right)\right)$. The computed loss values are fed into the adversarial training process to improve the layout design process. Then, the min-max loss value is estimated using Equation (3):

$$\min_G \max_D\left(G, D\right) = \left[\mathrm{E}_{xp_{data}}\left[\log D\left(x\right) + \mathrm{E}_{zpz_{(z)}}\log\left(1 - D\left(g\left(z\right)\right)\right)\right]\right]. \tag{3}$$

In Equation (3), *G* is denoted as a generator, *D* is a discriminator, and actual data is represented as xp_{data} which is gathered from the distribution of accurate data. Then, *z* is represented as the random noise sample obtained from the previous distribution. $D\left(x\right)$ denotes the discriminator's probability of accurately classifying genuine material as authentic. The term $D\left(g\left(z\right)\right)$ represents the probability that the discriminator correctly classifies the generated data as accurate. The training process involves generator *G*, aiming to maximize the realism score assigned by *D* to its synthetic layouts. At the same time, *D* attempts to reduce classification mistakes in recognizing G's counterfeit designs. The feedback mechanism ensures that the generator's output aligns with all input circumstances simultaneously. The emerging method combines landscape designs that achieve a harmonious equilibrium between fulfilling strict requirements and exploring innovative spatial potentials. The developed GAN-based landscape layout is collision-free and physically valid. The GAN model is designed to develop landscape layouts that match 3D site data input. The generator network receives structured spatial tensors representing three-dimensional site features like topography, elevation, and boundary conditions. The generator may create plans that match the site's natural characteristics and allowed use zones by integrating these inputs with zoning limitations, practical demands, and aesthetic choices. A voxel- or grid-based format that takes real-world dimensions into consideration may ensure that the output layout is physically plausible and contextually tailored to the input location's geometry.

Table 2 shows layout quality criteria including coverage, alignment, clustering, open space ratio, intersection density, etc. for several layout instances. Instead, we feed the GAN test cases with varied site configurations and average or sample the statistics. The evaluation set's site inputs follow functional and zoning requirements to test the GAN's generalizability and quality across multiple urban environments. Thus, Table 2 compares layout generation performance over a typical benchmark of test circumstances, not a single site instance. It shows model output robustness and spatial coherence. Validating their accomplishment requires a unique assessment procedure with location-specific results.Then, the sample layout quality analysis results are shown in Table 2.

Table 2. Layout quality analysis

Metric	Sample values
Coverage	0.56, 0.68, 0.79
Alignment	0.834, 0.92, 0.97
Density	13, 19, 24 buildings/km^2
Clustering	0.36, 0.57, 0.76
Open space ratio	0.3, 0.5, 0.2
Road length	2600 m, 3700 m, 4200 m
Intersection density	13,17,22 intersection/km^2
Distance to nearest neighbour	50 m, 40 m, 60 m
Fractal dimension	1,3, 1.62, 1.93
Land uses in mixed	0.3, 0.5, 0.8

The outcomes from various quantitative measurements suggest that the GAN models are generating urban plans that are both valid and realistic (Table 2). The coverage values range from 0.56 to 0.79, indicating a moderate to high density of buildings. Meanwhile, alignment scores between 0.834 and 0.97 suggest a grid-like arrangement. The thickness of buildings in this area ranges from 13 to 24 per square kilometre, showing a moderate dispersion to aggregation pattern. The open space ratios range from 0.2 to 0.5, indicating a proportionate distribution of developed and undeveloped areas. Roads spanning from 2600 to 4200 meters in length provide connectedness, aided by junction densities that allow for the creation of walkable blocks. The normal nearest neighbour distances in metropolitan areas range from 40 to 60 meters. The intricacy and organic patterns of the layouts may be quantified by fractal dimension values ranging from 1.3 to 1.92. Ultimately, the combination of use ratings reveals a distinct and identifiable variability in land use. These measurements indicate that the landscapes created by GANs possess genuine qualitative and quantitative characteristics about several urban planning and design variables. By comparing several indicators, one can obtain a more thorough evaluation of the plan's quality. The created GAN-based urban space landscape layout has been analyzed further using the Reinforcement Learning (RL) algorithm to maximize accessibility, usage, and safety.

3.5. Layout analysis using Reinforcement Learning (RL)

Reinforcement learning (RL) methods utilize iterative and experimental interactions in a simulated environment to identify optimum responses that maximize a specified reward function. The objective here is to improve the accessibility, utilization, and safety of greenspaces by adjusting their layout. The RL agent begins the process by generating a straightforward 3D environment with unoccupied areas and fundamental facilities. The layout iterations are created randomly and alter characteristics such as the location of walking paths, clusters of vegetation, and additional fixtures. The analysis is conducted based on a proximity cost function, which aims to balance the connections between elements and optimize space utilization efficiency. During each successive arrangement, the virtual park guests are simulated as they go across the region. Their movement patterns and measurements of space usage offer insights into the ease of travel and attendance in different areas. The safety evaluation module detects and highlights any instances of crashes or traffic obstruction. The simulation conducts several trials, systematically adjusting the layout components after each iteration depending on the recorded accessibility metrics, attendance, and collision incidents. The reward function optimization is influenced by these multi-criteria measures, prioritizing more inclusive utilization, improved linked navigation flows, and holistic reduction of tripping hazards. The continual reinforcement learning tuning progressively enhances the equilibrium of these three public health objectives until an ideal arrangement arises that optimizes the weighted cumulative reward score. The completed schematic incorporates crucial safety-tested enhancements designed for the distinct spatial environment. This AI-driven simulation method enhances an evidence-based understanding of the complex interactions among design features, use patterns, and health risks, enabling layout solutions tailored to visitor's needs.

The reinforcement learning agent begins by initializing the layout policy parameters θ. These parameters define the items that can be placed, such as benches, lighting, and pavement tiles, which comprise the created landscape. During each episode simulation, these pieces combine to form new layout permutations. Virtual Park visitors then navigate through these permutations while monitoring the ease of accessibility, attendance levels in different zones, and any instances of collisions. The utilization measurements are converted into scalar reward terms. The word r_{usage} represents usage rates across different locations, r_{access} represents navigation flow and r_{safety} penalizes dangers. The safety priority scale α assigns weights to risks to emphasize their urgency. The reward function $J(\theta)$ is formed by summing the three elements, and the algorithm aims to maximize this function via repeated rounds (Equation 4).

$$\left.\begin{aligned} r_{usage} &= \frac{usage}{attendence\,reward} \\ r_{access} &= \frac{ease\,of\,use}{navigation\,reward} \\ r_{safety} &= penalties\,for\,collisions\,and\,hazards \\ \alpha &= scaling\,factor\,for\,safety\,and\,priority \\ J(\theta) &= r_{usage} + r_{access} + \alpha \times r_{safety} \end{aligned}\right\}. \quad (4)$$

Following each layout simulation, the agent adjusts the weights of the policy parameters θ following the gradient of the reward score $\nabla\theta J(\theta)$. The parameter α, which controls the safety objective weight in the RL reward function, was chosen after reviewing urban safety studies and public health planning guidelines that prioritize visibility, surveillance, and accident reduction in park and streetscape design. A basic value of α = 0.5 was empirically calibrated by grid search across simulation settings to balance safety, accessibility, and consumption. Later in training, α was modified dynamically utilizing a feedback-based normalizing method to optimize objectives fairly based on convergence rates and gradient magnitudes. This process progressively changes the arrangement of elements, enhancing overall health results. Minute adjustments to individual elements propagate across several quick simulations under the guidance of signals related to usage, accessibility, and safety. The initial arbitrary alterations transition into refined strategic positioning, which carefully balances specific advantages and concealed disadvantages. Ultimately, the layout iterations reach a stable optimum solution that optimizes the cumulative weighted reward Equation (5).

$$\theta \leftarrow \theta + \alpha\nabla\theta J(\theta);\;\; J(\theta) = E[R]. \quad (5)$$

The RL optimizes the distribution of attendees, ensures easy navigation access, and reduces potential dangers under health guidelines. The optimum layout, which is ready for building, is generated by the final policy parameter set θ. The AI agent utilizes virtual trial and error and gradient-based policy tweaking to learn park layouts to maximize several health and safety objectives. Integrating natural elements and vegetation into urban surroundings through landscape design can enhance the health and wellness of individuals. Supervised machine learning algorithms like support vector machine, *k*-nearest neighbouring approach, random forest and neural networks may be utilized to identify public health data and disease outbreaks. This enables towns to take pre-emptive measures by allocating resources and implementing suggestions to mitigate the spread of diseases. In addition, the supervised techniques explore a person's health, food preferences and lifestyle factors to create a personalized nutrition chart and food recommendations that help to reach their health goal. Further, the AI assist-based developed landscape consists of intelligent shopping assistance that utilizes grocery store barcodes. The intelligent system provides feedback on selected food choices that help manage nutritional deficiencies. Thus, the effective utilization of artificial intelligence in urban cities' landscape architecture improves people's health decision-making. Then, the system's effectiveness is evaluated using an accessibility metric, which helps compute the average travel distance between the number of access points, walkable routes, and essential health key locations. The lower travel distance and maximum connectivity represent that GAN and RL-based created landscape structures ensure better accessibility. Then, the graphical analysis of accessibility for various distances is shown in Figure 3.

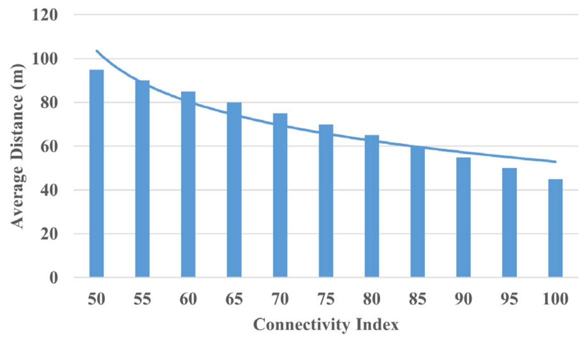

Figure 3. Accessibility analysis

The utilization of a generative adversarial network (GAN) and reinforcement learning technique enables the achievement of accessibility measures such as reduced average journey lengths and increased connection indices in the creation of landscape layouts. By adjusting the essential hyperparameters of GAN and RL, the system's resiliency was evaluated. The GAN gradient penalty coefficient, learning rate, and latent vector size were adjusted. Since tiny rates inhibited convergence and larger values caused instability, moderate rates (e.g., 0.0001–0.0002) generated the most stable outcomes. To test the layout quality, several incentive weights (usage, accessibility, and safety) in the RL framework. When safety was overemphasized, accessibility decreased, but the system maintained stability with modest weight movements. They indicate that the system can manage tiny parameter changes, but fine-tuning is needed to keep layout development balanced and high-quality.The GAN enables the generation of several potential layouts by acquiring knowledge from actual landscape designs. It generates diverse solutions by arranging routes and placing access points differently. Subsequently, a reinforcement learning agent systematically assesses and enhances the arrangements by traversing them to reduce the distance travelled, using a reward function. The agent optimizes its overall reward over an extended period by investigating alterations that enhance movement and entry. The agent can create layouts with more connections, more efficient paths, and shorter distances between essential spots through a series of iterations, including produced designs and virtual travel. The training approach results in optimized landscape structures that achieve high scores on accessibility metrics. The emergent plans demonstrate a reduction in average trip lengths, with around 50 m compared to the earlier designs' 95 m. Additionally, they attain a greater level of route connectedness, with indices approaching 100 instead of the original value of 50. This exemplifies the capacity of the AI generative system to proficiently acquire and enhance accessibility objectives, generating legitimate landscape designs customized for facilitating navigation and utilization. The GAN-RL technique shows potential in creating landscape designs that are easily accessible. Then, further excellence of the GAN-RL-based landscape architecture design is evaluated using experimental results and compared with existing techniques.

GAN and RL components were constantly supervised throughout training using multi-criteria convergence thresholds to ensure optimality and convergence. GAN convergence was evaluated by stabilizing adversarial loss (*LGAN*), constraint loss (*Llayout*), and health-aligned loss (*Lhealth*) over successive epochs. Training was stopped after losses achieved a plateau of ±1% variance over 20 consecutive epochs, since neither generator nor discriminator showed dominance. Tracking arrangement characteristics like alignment and coverage (Table 2) confirmed realistic output stability. The cumulative reward function in Equation (4) had to stable across episodes for the RL agent to converge. The agent was considered convergent if the change in average cumulative reward across a 50-episode rolling window was smaller than a predefined delta ($\Delta R < 0.001$). Early pausing and sometimes exploration restarts prevented local minima and premature convergence. Averaging the highest validation reward over numerous simulated circumstances determined the final policy. We used multi-layered convergence to ensure that the GAN and RL components performed well in terms of layout practicability, health goals, and spatial quality. For functional coherence, a spatial verification approach verified path connectivity, proximity limitations between facilities (such seats near walkways), and zoning boundary compliance after the GAN developed each layout. All of these tests used graph-based traversal and distance to verify spatial connections. The model learned to avoid invalid layouts during iteration because constraint-aware feedback mechanisms automatically removed or punished incorrect layouts during training. Dimensionality optimisation was applied during preprocessing to address high-dimensional and sparse data. PCA was used to decrease non-spatial input data including functional demands and artistic preferences. It preserved the most critical variance and removed extraneous elements. For spatial data, downsampled grid representations contained zoning and topography inputs. These representations preserved spatial organization while minimizing resolution overhead. The model's capacity to find significant patterns without irrelevant or sparse input improved training efficiency and generalizability. We used these methods to ensure that the GAN and RL components worked effectively across multiple sites without compromising performance or scalability.

To test the model, used the site inputs from real-world GIS datasets that had parcel geometries that were not perfectly rectangular, had fractured land plots, and had skewed borders.

- The GAN generator successfully adapted by conditioning on terrain grids and spatial zoning masks, which enabled it to produce workable layouts even when working with limited or asymmetrical site limits.
- RL Navigation: By modifying its reward gradients and collision avoidance methods, the RL agent was able to maximize mobility and amenity placement in irregular layouts, while preserving accessibility and safety.
- Regardless of the non-standard lot forms, all of the produced layouts maintained zoning compliance, functional connection (such as linked paths), and amenity clustering.
- There was no structural failure identified, although there was a little decrease of around 8% in reward convergence speed and layout compactness in parcels that were very fragmented or narrow.

The model's robustness and flexibility in the face of non-standard urban situations lend credence to its potential use in such settings.

4. Experimental results

This section discusses the GAN- and RL-generated landscape architecture design for managing health decisions. The landscape layout has been generated with the help of the generator and discriminator networks. The network reduces the false prediction of landscape used to improve the overall data analysis process. The gathered information is explored using a generator, and decoding is performed to get the discriminator information. Afterwards, the layout has been created by comparing the actual data samples. The min-max loss function is estimated to predict the error or deviation between the output values. According to the output value, network parameters are fine-tuned to improve the overall results. Then, RL is applied to maximize the safety and usage of layouts, which is performed up to many iterations to develop effective layouts. Finally, the health decision systems and recommendations are incorporated with the landscape layouts to improve the overall efficiency of the urban region. During the analysis, OpenStreetMap (https://welcome.openstreetmap.org/working-with-osm-data/downloading-and-using/) information is utilized to obtain the particular region input. This site provides the raw data of the country's information and specific features such as buildings, roads. This paper uses OSM data since it is free, has a consistent geographic organization, and can be utilized for scaled training in many urban situations. Higher-resolution geographic data (e.g., LiDAR, municipal GIS layers) is needed to train large-scale models, but it is computationally expensive, unreliable, and proprietary. This data provides further information. OSM can replicate macro-scale urban features including roads, building footprints, and land use zones for planning-level layout design. Due to OSM data's poor resolution, the model may not be able to depict fine-scale characteristics such microscopic plant barriers, sub-meter pedestrian pathways, or ground undulations. This hinders GAN learning of complicated spatial compositions and RL agent accessibility and safety dynamics. OSM data offers powerful, transferable layout synthesis in multiple city contexts by concentrating on generalizability and computational tractability, etc.

Python with TensorFlow for the GAN component and PyTorch for the RL module was used to create the GAN-RL framework on an NVIDIA RTX A6000 GPU with 48 GB RAM. The average GAN epoch training duration was 2.3 minutes, and convergence took 120–150 epochs. RL modules trained over 2,000 episodes each scenario took 5 hours per cycle. The safety component was given a larger weight ($\alpha = 0.5$) in the reward function to prioritize risk minimization in early iterations. However, a dynamic weighing approach was used to balance safety, usefulness, and accessibility. A normalization technique was used to alter α based on convergence rate and reward saturation, ensuring no one aim dominated the learning process. The adaptive balancing ensured equal gains across all health-aligned targets throughout optimization.

Multi-channel grid maps incorporated spatial and legal limitations into tensors, with each channel representing a zoning ordinance or functional necessity. Buildable zones were binary masks (1 for allowed, 0 for prohibited), whereas distance buffers surrounding protected locations (e.g., water bodies, schools) were continuous distance maps normalized between 0 and 1. Relational matrices recorded functional adjacency requirements (e.g., seats near passageways), with higher scores indicating stricter design limitations. Municipal zoning rules and planning manuals inform these tensors, which match urban GIS layers.

The collected information is analyzed according to Figure 1, and the layouts are designed to improve the efficiency of the urban space. The GAN and RL-based developed layout is compared with the existing methods such as Deep Learning Networks (DLN) (Pala et al., 2020), Fuzzy Decision Systems (FDS) (Jahani & Rayegani, 2020) and Long Short Term Memory Networks (LSTM) (Yu et al., 2023). Then, the system's efficiency is evaluated using accessibility, usage, safety and aesthetics analysis.

Due to their experience in urban planning, environmental modeling, and health-related layout prediction, the DLN, FDS, and LSTM models were chosen. General-purpose deep models utilized in spatial reasoning include DLN, while interpretable rule-based systems are represented by FDS, and LSTM captures temporal or sequential layout decisions, such as pedestrian flows or changes in urban environments. These benchmarks provide multiple architectural paradigms for a balanced generative-reinforcement framework comparison.

4.1. Accessibility analysis

Figure 4 illustrates the accessibility analysis of the introduced AI techniques, such as GAN and RL-based landscape architecture plans. The analysis is computed by examining the relationship between the average travel distance and the connectivity index. The results obtained are compared with existing works such as Pala et al. (2020), Jahani and Rayegani (2020), and Yu et al. (2023). GANs, combined with RL, enables the model to enhance intricate spatial connections through simulation by exploring various designs and utilizing direct training signals for accessibility rewards. This emerging AI technique effectively scales by adjusting layouts to accommodate accessibility constraints and uncovering innovative solutions that enhance navigation and access, surpassing the limitations of manual design. With an increase in the connection index from 50 to 100, the average trip distance falls for layouts from all the models, indicating a positive correlation between route connectedness and improved accessibility. The GAN+RL model exhibits superior performance in minimizing travel distances. Specifically, it achieves a distance of 95 m when the connection index is set at 50 and reduces it to 45 m when the index is increased to 100. This shows the superior effectiveness of the GAN+RL technique in optimizing accessibility. The DLN model has the most significant average journey distances, varying between 106m and 66m over the index range. The FDS and LSTM models produce intermediary outcomes between the DLN and GAN+RL methodologies. The GAN+RL configuration, with a connection index of 75, has an average distance of 70 m. In comparison, the LSTM layout has an average distance of 80 m, the FDS layout has an average distance of 79 m, and the DLN layout has an average distance of 86 m. The GAN+RL model has a distinct superiority.

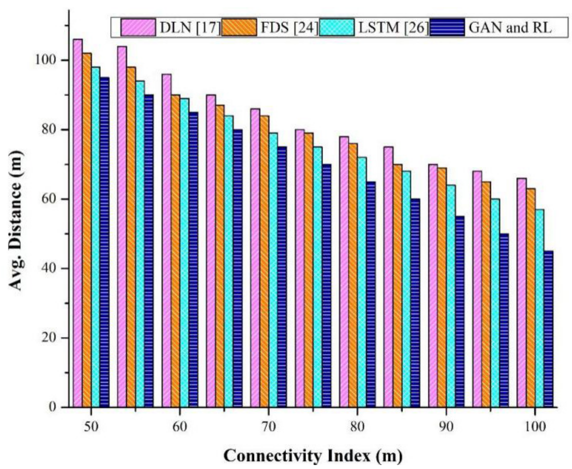

Figure 4. Accessibility analysis

4.2. Usage analysis

The GAN+RL model outperforms other approaches, such as DLN, FDS, and LSTM, to achieve the highest peak occupancy rates at each period (Figure 5). At 10 am, the GAN+RL architecture exhibits the highest utilization rate of 82%, compared to 75% for the DLN, 68% for the FDS, and 79% for the LSTM models. GAN+RL demonstrates superior optimization of urban layouts for high utilization and density at various times of day, utilizing its generative and reinforcement learning methodology. The utilization of GANs to explore different layouts provides the RL agent with a wider variety of choices to optimize the arrangement of functional spaces that encourage usage. The RL model learns to create layouts that effectively distribute and orient areas based on demand for use at different times, directly incentivizing higher occupancy rates through simulation. The emerging solutions are designed to adjust to the ever-changing patterns of urban life, resulting in intricate spatial interactions that ensure continuous and efficient use of areas throughout the day. This data-centric generative technique surpasses alternative methods by intentionally optimizing space use.

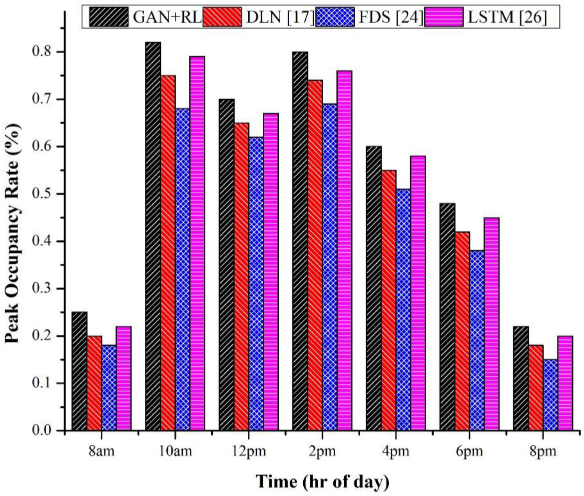

Figure 5. Usage analysis

4.3. Safety analysis

The visibility index positively correlates with the amount of open space in the layouts, enhancing sight lines and supervision and improving safety (Figure 6). The GAN+RL model consistently achieves greater visibility in every scenario. At a visibility ratio of 0.5, GAN+RL achieves an index of 0.82, compared to 0.77 for DLN, 0.73 for FDS, and 0.79 for LSTM. This showcases the capacity of GAN+RL to optimize layouts by prioritizing open areas, maintaining balanced building arrangements, strategically placing viewpoints, and considering other design elements that improve security and safety. The emerging solutions also enhance healthy decision-making by minimizing hidden spaces that may foster illegal actions, therefore inherently increasing safety through intentional design. The GAN's investigation of many designs offers the RL agent a more comprehensive range of choices to optimize visibility. The RL model learns to avoid dangerous configurations by providing explicit rewards for layouts with increased supervision, fewer hidden areas, and clear lines of view.

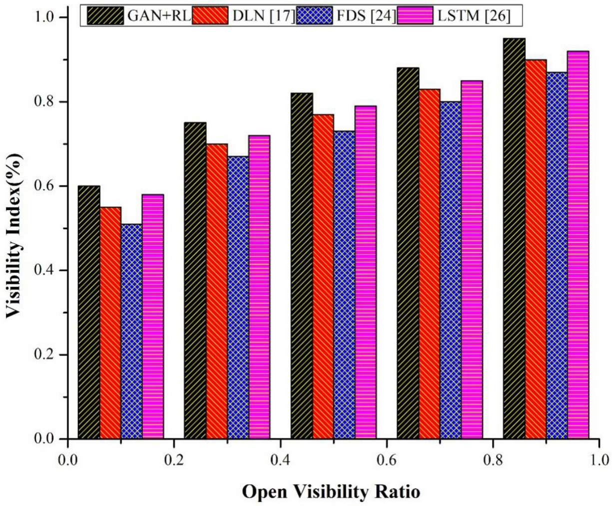

Figure 6. Safety analysis

The simulation of pedestrian movement instructs the agent to eradicate isolated regions and allocate perspective points strategically to include the entire layout. This process of emergence generates environments that possess intrinsic natural surveillance. The model considers immediate and subsequent effects, enhancing comprehensive safety by considering interconnected aspects such as illumination, path widths, and landscaping. This enhances consumers' ability to make sound decisions. The scalable data-driven method outperforms human capacity in managing safety issues by overcoming biases that may lead to neglecting unsafe designs. This progress stimulates the creation of inherently more beneficial designs.

4.4. Aesthetics analysis

The layout's level of interest and aesthetic attractiveness progressively improves with each subsequent training episode for all the models (Figure 7). The GAN+RL tech-

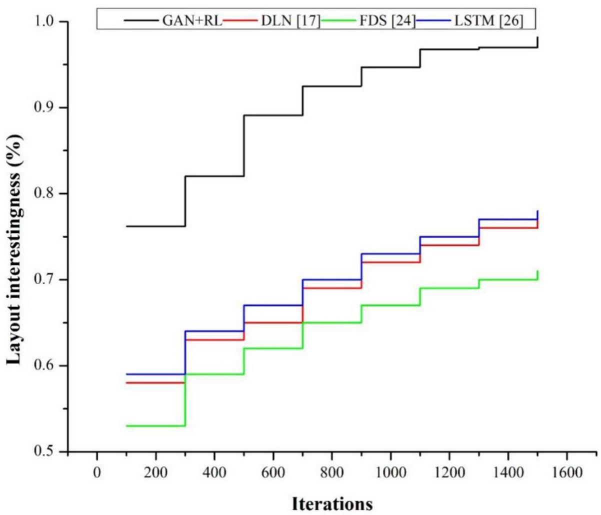

Figure 7. Aesthetic analysis

nique consistently attains greater levels of interestingness at every stage. After 1000 iterations, the GAN+RL model achieves an interestingness score of 0.96, whereas the DLN model scores 0.74, the FDS model scores 0.68, and the LSTM model scores 0.72. The combination of GAN and RL is effective in optimizing aesthetics. GAN allows for exploring new ideas, while the RL agent learns intricate visual preferences from human feedback through repeated training. Thus, the introduced GAN and RL-based developed urban landscape layout effectively adapts to the environment and helps to provide guidelines while handling health decisions with maximum efficiency.

5. Discussion

GAN and RL models stopped early based on validation loss and reward stagnation to reduce overfitting. During training, a 20% validation split was employed to assess performance using structural layout quality measures including clustering and open space ratio that were not optimized in the loss function. After 100 episodes, the RL module stopped training when the cumulative reward moving average flattened. Generalization was improved via dropout layers and data supplementation (e.g., rotated or mirrored zoning maps). Rotating through site configurations from different geographic regions allowed minimal cross-validation.

The GAN-RL framework was tested on urban locations from 1 km^2 to 20 km^2, including both small and large park spaces, to ensure scalability. As spatial dimensions increased, training duration, incentive convergence, and layout quality remained consistent, while computing cost increased linearly. Plans were also created for five future cities with differing grid complexity, building densities, and topographies. The model's continuous performance patterns indicated its capacity to generalize across urban sizes.

Semantic layout maps from GAN outputs color-code and identify each zone (e.g., pedestrian pathways, green spaces, sitting places). This helps urban planners understand how the design meets functional and health goals (e.g., open space ratios, social interaction zones).

Highlighting Health Features: Visibility, green buffer zones, and walkability corridors are highlighted in the system for health benefits. Post-processing modules evaluate layout tensor spatial distributions to extract these areas.

RL Reward Heatmaps: The RL agent shows which safety, utilization, and accessibility factors contributed most to cumulative reward. This shows how health incentives influence agent behavior.

Saliency Analysis: Saliency maps show which input factors (zoning, landscape) most affected layout features for GAN interpretability. This explains generator design choices. Rule-Based Auditing: Final layouts undergo rule-based spatial audits to ensure compliance with health-related limitations (e.g., minimum path lengths, proximity to amenities) and provide interpretable compliance results.

These methods are transparent and interpretable, allowing stakeholders to evaluate and trust AI-generated designs in health-sensitive urban planning.

GAN-RL outperforms DLN, FDS, and LSTM in flexibility and robustness. GAN learns complex spatial patterns while preserving design viability under changing site geometries and zoning restrictions, unlike static rule-based or sequential models. Since the RL agent continuously adapts layouts through feedback-driven optimization, the system can reliably operate in unequal parcel shapes, fragmented zones, or competing objectives (such as safety vs. accessibility). Real-world planning applications with heterogeneity and uncertainty benefit from this dual-learning architecture's resilient performance across diverse urban configurations, consistent layout quality, faster convergence, and greater tolerance for sparse or imbalanced data inputs.

6. Conclusions

An AI-driven system that automates health-sensitive urban landscape design by integrating GAN and RL is presented in this paper. With a visibility index of 0.82 and an interest score of 0.96, the model does an excellent job of optimizing space layouts for accessibility, usability, aesthetics, and safety. The technology integrates computational design with public health goals by encoding health principles and legal zoning limits into trainable forms. When it comes to unusual parcel configurations in particular, the GAN-RL framework demonstrates better flexibility than baseline models (DLN, FDS, LSTM). The key innovation is the combination of deep generative modeling with multi-objective reward optimization to direct data-driven city planning within practical limitations. Here we have a method that can be easily replicated and expanded upon to include AI into public landscape design while simultaneously attending to its shape and purpose. The use of OpenStreetMap, a medium-resolution geographic dataset, is one of the restrictions. Another is the possibility of cultural bias in the training samples. Lastly, the zoning logic is peculiar to a certain location. Furthermore, post-occupancy evaluation and dynamic engagement with actual user input are missing from the present architecture. Incorporating public sentiment models, finer-resolution geographical information, and local planning restrictions into the system will be the focus of future study as it is being extended to varied global cities. Improving openness and flexibility through the integration of interpretable AI components and real-time sensor data will create health-oriented urban landscapes that are more inclusive and responsive.

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Availability of data and materials

The data used to support the findings of this study are all in the manuscript.

Disclosure statement

The authors declare that they have no conflicts of interest to report regarding the present study.

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