International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Construction of Multi-objective Optimization Model for Landscape Health Activity Space Design

Yu Zhang[1+], Daogu Nie[1]

Submitted: 24/09/2023 **Revised**: 15/11/2023 **Accepted**: 27/11/2023

Abstract: Space design is to create spaces that cater to the needs and preferences of the people who will use them. This can involve designing residential spaces such as homes and apartments, commercial spaces like offices and retail stores, and public spaces such as museums, libraries, and recreational areas. This paper presents a novel approach for Landscape Health Activity Space Design, with Reliability Multi-Objective Optimization (RMOO) to create sustainable and user-centric outdoor environments that promote physical activity and mental well-being. The RMOO model computes a balance between greenery density, pathway length, and accessibility while considering budget constraints. Through the RMOO process, a diverse set of Pareto solutions was obtained, offering decision-makers multiple landscape design options to choose from. The proposed RMOO model uses the Pareto optimization model with the computation of the multi-optimization factors. Sensitivity analysis was conducted to assess the robustness of the solutions to uncertainties, aiding in the selection of stable design configurations. Convergence analysis demonstrated the optimization algorithm's effectiveness in improving solutions over generations. The simulation environment confirmed the proposed designs' positive impact on physical activity and mental well-being, enhancing the overall landscape health. The RMOO approach offers a valuable tool for designing healthier and more sustainable outdoor spaces, contributing to improved public well-being and a greener future.

Keywords*: Multi-Objective Optimization, Health Benefits, Space Design, Reliability Computation*

1. Introduction

Landscape Health Activity Space Design is a holistic approach that integrates landscape architecture, health and wellness principles, and activity planning to create outdoor spaces that promote physical activity, mental well-being, and overall health for users [1]. This design philosophy recognizes the profound influence of the natural environment on human health and seeks to harness the therapeutic potential of outdoor spaces. With blending active design, biophilic elements, inclusivity, and sustainability, Landscape Health Activity Space Design aims to enhance the quality of life, foster community engagement, and nurture a profound connection between people and nature. Through this innovative approach, individuals can experience the numerous health benefits of spending time in thoughtfully designed outdoor environments, contributing to healthier, happier, and more vibrant communities [2]. Landscape Health Activity Space Design takes a comprehensive and interdisciplinary approach to create outdoor spaces that go beyond traditional aesthetics and functional considerations. It recognizes that the built environment has a profound impact on human health and well-being, and by purposefully integrating health-promoting elements into the landscape, it can enhance the overall quality of life for individuals and communities [3].

One of the fundamental principles of Landscape Health Activity Space Design is the promotion of physical activity [4]. The design of landscapes and outdoor spaces is carefully planned to encourage movement and exercise. This can include the incorporation of walking and cycling paths, jogging trails, fitness stations, sports facilities, and open green spaces for recreational activities. With providing opportunities for physical activity, the design supports active living and addresses sedentary lifestyles, which are linked to various health issues [5]. Incorporating biophilic elements is another key aspect of Landscape Health Activity Space Design. Biophilia refers to the innate human connection with nature, and incorporating natural elements into the landscape, such as greenery, water features, and natural materials, can have numerous positive effects on human well-being. Exposure to nature has been shown to reduce stress, improve mood, boost cognitive function, and enhance mental health [6]. Through creating landscapes that foster this connection with nature, Landscape Health Activity Space Design contributes to a sense of peace and tranquility. Accessibility and inclusivity are crucial considerations in the design process. Outdoor spaces are designed to be welcoming and usable by people of all ages, abilities, and backgrounds [7]. Wheelchair-accessible pathways, seating areas, and sensory gardens are examples of elements that promote inclusivity and ensure that all individuals can benefit from the health-promoting aspects of the environment.

[1] *Art Department, International College, Krirk University, Bangkok 10220, Thailand*
Corresponding Author: hebeimeiyuanzhang@163.com

Therapeutic landscapes play a vital role in Landscape Health Activity Space Design. These are spaces intentionally designed to provide opportunities for relaxation, contemplation, and stress reduction. Healing gardens, meditation areas, and spaces for mindfulness activities are integrated into the landscape to provide a respite from the fast-paced urban environment and promote mental well-being [8]. Safety and security are paramount considerations in the design process. Adequate lighting, clear wayfinding, and the identification and mitigation of potential hazards ensure that users can comfortably and safely navigate the outdoor space, contributing to a sense of security and well-being. Sustainability is at the core of Landscape Health Activity Space Design [9]. The use of environmentally friendly practices, such as native plantings, rainwater harvesting, and renewable energy sources, ensures that the design supports not only human health but also the health of the environment [10].

Landscape Health Activity Space Design strives to create outdoor spaces that promote physical activity, mental relaxation, and social interaction while fostering a sense of community and connection with nature [11]. Through prioritizing the health and well-being of users and the environment, this approach to landscape design contributes to the creation of vibrant, resilient, and sustainable communities that prioritize the health and happiness of their residents [12]. Landscape Health Activity Space Design, coupled with deep learning, represents a groundbreaking approach that harnesses the power of artificial intelligence to create outdoor environments that not only promote physical activity and mental well-being but also continuously adapt to optimize health outcomes. Deep learning, a subset of machine learning based on artificial neural networks, has the potential to revolutionize the way of design and manage outdoor spaces [13]. Through integrating deep learning algorithms into Landscape Health Activity Space Design, can create smart and dynamic landscapes that respond to user needs, environmental conditions, and health data. This innovative synergy opens up new possibilities for enhancing human experiences, improving public health, and advancing sustainability in outdoor spaces [14]. In this paper, presented the transformative potential of integrating deep learning into Landscape Health Activity Space Design and explore the various applications and benefits this powerful combination offers for creating healthier and more resilient communities.

2. Review of the Multi-Objective Model

This section presented the existing paper focused on the heath activity design with the uses of Artificial Intelligence (AI) techniques. In [15] demonstrates how machine learning algorithms can efficiently explore the vast protein sequence space, identifying variants with desired functionalities and characteristics. This has significant implications for drug discovery and biotechnological applications, as it can accelerate the engineering of proteins for specific purposes. In [16] highlights the potential of machine learning in materials discovery and innovation. Through machine learning to analyze vast materials databases and predict material properties, researchers can expedite the identification of novel materials for various applications, revolutionizing materials science and engineering.

In [17] employs deep learning algorithms to understand human perceptions of playability in urban environments. The study identifies factors influencing playability, such as green spaces and playgrounds, which can inform urban planning and design to create more engaging and user-centric public spaces. In [18] investigates how visual exposure in high-density urban environments affects pedestrian emotions. By analyzing images and using machine learning, the study provides insights into urban psychology and well-being, helping urban planners and architects design spaces that promote positive emotions and mental well-being. In [19] offers an overview of machine learning applications in embedded and mobile systems. The study explores optimizations and applications of machine learning for smart devices, paving the way for more efficient and intelligent embedded systems. In [20] examines house price appreciation using machine learning algorithms and big geo-data. The study contributes to real estate and urban development planning, enabling better understanding of factors influencing property prices.

In [21] utilizes multi-objective optimization and agent-based modeling for space layout planning. The research aids in creating efficient and user-friendly building designs that consider various occupancy scenarios. In [22] focuses on optimizing physical activity spaces to promote health and active living. Multi-objective optimization enables designers to create spaces that encourage physical well-being and fitness. In [23] uses multi-objective optimization for public space canopy design, considering shading, structural integrity, and social performance. The research contributes to creating comfortable and functional public spaces. In [24] explores the use of multi-objective optimization for sustainable tourism planning. The study aids in developing tourism strategies that balance economic, environmental, and social goals. In [25] investigates participatory multi-objective optimization for sustainable urban development. The study promotes the creation of dense and green cities that meet diverse urban needs. In [26] applies multi-objective optimization to high-rise building layout design. The research aims to optimize daylight, visual comfort, and outdoor thermal performance, contributing to sustainable and user-centric building design. In [27] explores multi-objective optimization and agent-based conflict resolution in marine spatial planning. The research aids in sustainable marine resource management and conservation. In [28] focuses on multi-objective optimization for urban environmental system design. The study contributes to creating smarter and more sustainable urban environments that optimize various environmental metrics.

These studies showcase the transformative potential of these technologies in addressing complex challenges and promoting sustainability, efficiency, and user-centric solutions. From accelerating drug discovery in biotechnology and revolutionizing materials science to enhancing urban planning by understanding human perceptions and emotions, the papers highlight the diverse applications and benefits of machine learning and optimization techniques. Additionally, the integration of multi-objective optimization in urban planning, building design, tourism sustainability, and environmental management offers a multi-faceted approach to address complex urban and environmental challenges. Overall, the literature provides valuable insights and methodologies that can inform future research and decision-making, contributing to a more sustainable and efficient future for society and the environment.

3. Landscape Health Activity Space Design

Landscape Health Activity Space Design with Reliability Multi-Objective Optimization (RMOO) is an innovative approach that combines the principles of Landscape Health Activity Space Design with the power of multi-objective optimization, considering reliability as an additional criterion. RMOO seeks to create outdoor spaces that not only promote physical activity, mental well-being, and overall health but also ensure the robustness and reliability of the design under various conditions and uncertainties. In traditional Landscape Health Activity Space Design, the focus is on creating spaces that foster physical activity, enhance mental well-being, and encourage social interaction, while incorporating biophilic elements and sustainability practices. However, the design process may not explicitly account for uncertainties in the environment, usage patterns, or changing needs over time. Reliability Multi-Objective Optimization extends this approach by introducing reliability as an additional objective. RMOO involves optimizing the design of outdoor spaces while considering multiple competing objectives, such as promoting physical activity, enhancing well-being, and fostering social interactions, while also ensuring that the design is robust and reliable under different scenarios. To achieve this, RMOO employs advanced optimization algorithms that explore the design space and identify the optimal solutions that achieve a balance between the various objectives while considering uncertainties and potential risks. The consider factors like extreme weather conditions, fluctuations in user preferences, and the long-term durability of the design as shown in figure 1.

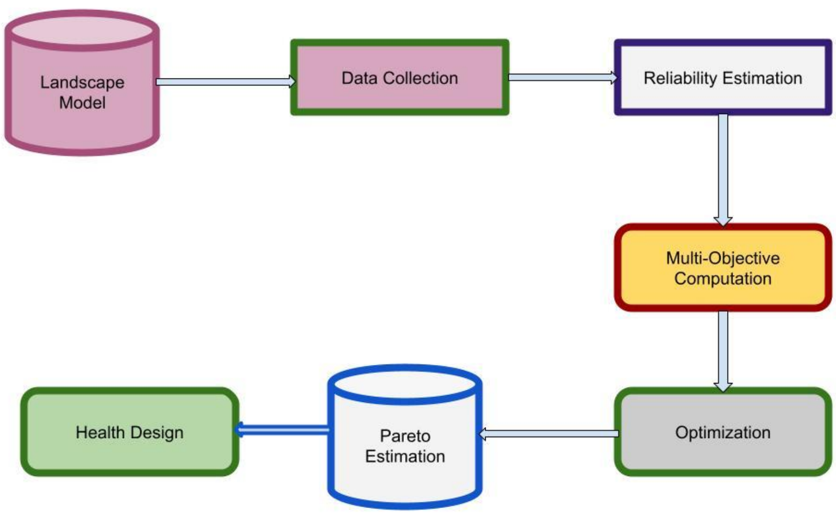

Fig 1: Steps in RMOO

Formulating Reliability Multi-Objective Optimization (RMOO) for Landscape Health Activity Space Design involves defining decision variables, objective functions, constraints, and considerations for reliability. Here's a generalized formulation:

Decision Variables (x): Decision variables represent the design parameters that can be adjusted to create the landscape health activity space. These variables can include the location of pathways, the size of recreational areas, the selection of greenery and materials, seating arrangements, and other design elements. The decision variables are represented as a vector, $x = [x1, x2, \ldots, xn]$, where n is the number of decision variables.

Objective Functions (f): The objective functions quantify the goals to be optimized. In Landscape Health Activity Space Design, multiple objectives are considered, such as maximizing physical activity opportunities, enhancing mental well-being, promoting social interactions, and ensuring sustainability. The objective functions are represented as a vector, $f = [f1(x), f2(x), \ldots, fm(x)]$, where m is the number of objectives.

3.1 Constraints in RMOO

In Multi-Objective Optimization with Reliability (RMOO) for Landscape Health Activity Space Design, consider multiple objective functions and constraints, along with reliability considerations, to create robust and effective outdoor spaces. Consider the RMOO model for the computation of multi-objective optimization model,

Maximize Physical Activity (PA): Represented by $f1(x)$, where x is the vector of decision variables (design parameters).

Maximize Mental Well-being (MW): Represented by $f2(x)$.

Constraints:

Budget Constraint: $g1(x)$ represents the budget constraint for the design, ensuring that the cost of the design does not exceed a certain budget limit.

Accessibility Constraint: $g2(x)$ ensures that the outdoor space is accessible to all users, including those with mobility challenges. It guarantees that pathways, ramps, and facilities are designed to accommodate people with disabilities.

Safety Constraint: $g3(x)$ ensures the safety of users by placing lighting and security measures, minimizing tripping hazards, and adhering to safety standards.

Sustainability Constraint: $g4(x)$ promotes sustainable design by incorporating renewable materials, energy-efficient features, and water-saving mechanisms.

The uncertain parameters $\delta 1$ and $\delta 2$ to represent variations in physical activity and mental well-being. These uncertainties may arise due to changing user behavior, environmental conditions, or other factors affecting the effectiveness of the design. The reliability function $R(x)$ calculates the probability that the design meets specified performance criteria under these uncertainties are computed with equation (1)

$$R(x) = P[PA(x) \geq PA_{min}] * P[MW(x) \geq MW_{min}] \quad (1)$$

where PA_{min} and MW_{min} are the minimum desired values for physical activity and mental well-being, respectively. The RMOO problem with reliability consideration and multi-objective constraints can be formulated as in equation (2)

$$Maximize: F(x) = [f1(x), f2(x), R(x)] \quad (2)$$

Subject to: $g1(x) \leq Budget$

$$g2(x) \leq Accessibility\ Limit$$

$$g3(x) \leq Safety\ Limit$$

$$g4(x) \leq Sustainability\ Limit$$

To find the Pareto optimal solutions, with multi-objective optimization problem while considering the reliability and the multiple constraints. Specialized optimization algorithms and probabilistic models are used to explore the design space and identify the set of non-dominated solutions (Pareto front).

Table 1: Objective Function with RMOO

Objective Functions	**Constraints**	**Reliability Consideration**
1. Maximize PA	1. Budget: g1(x) ≤ Budget Limit	R(x) = P[PA(x) ≥ PA_min] * P[MW(x) ≥ MW_min]
2. Maximize MW	2. Accessibility: g2(x) ≤ Accessibility Limit	
	3. Safety: g3(x) ≤ Safety Limit	
	4. Sustainability: g4(x) ≤ Sustainability Limit	

In the table 1 above explained the objective functions, $f1(x)$ and $f2(x)$, represent maximizing physical activity (PA) and mental well-being (MW), respectively. The constraints $g1(x), g2(x), g3(x), and\ g4(x)$ correspond to the budget constraint, accessibility constraint, safety constraint, and sustainability constraint, respectively.

The reliability consideration $R(x)$ accounts for uncertainties represented by $\delta1$ and $\delta2$ in achieving the desired levels of PA and MW, respectively.

3.2 Defining Objective Function

Constraints represent the limitations and requirements that the design must satisfy. These constraints could include budget limitations, available land area, accessibility requirements, and safety standards. The constraints are represented as a set of functions, $g\_i(x) \leq 0\ for\ I = 1, 2, \ldots, p$, where p is the number of constraints. To incorporate reliability into the optimization, uncertainty factors are introduced. These could include uncertain parameters, probabilistic models representing environmental changes, user behavior, and weather conditions that may impact the effectiveness and longevity of the design elements. The uncertainties are modelling as probability distributions.

Trade-Off Analysis: RMOO aims to find a set of solutions that represent the Pareto front—a set of non-dominated solutions. The trade-offs between different objectives are analyzed to identify the best compromise solutions. The optimization seeks to maximize the objective functions while considering the reliability under uncertainty. The RMOO problem can be formulated as follows in equation (3) and equation (4)

Maximize: $f(x) = [f1(x), f2(x), \ldots, fm(x)]$

Subject to: $g_i(x) \leq 0, for\ I = 1, 2, \ldots, p$

Where x represents the decision variables, f(x) represents the vector of objective functions, and $g_i(x)$ are the constraint functions. Additionally, the reliability consideration involves incorporating probabilistic models for uncertainties that affect the performance of the design elements. Consider the following scenario for designing a landscape health activity space:

Maximize Physical Activity (PA): Represented by f1(x), where x is the vector of decision variables (design parameters).

Maximize Mental Well-being (MW): Represented by f2(x).

Budget Constraint: g(x) represents the budget constraint for the design, ensuring that the cost of the design does not exceed a certain budget limit.

The RMOO problem can be formulated as follows:

$$Maximize: f(x) = [f1(x), f2(x)]$$

$$Subject\ to: g(x) \leq Budget$$

Consider the reliability consideration introduce uncertain parameters $\delta1$ and $\delta2$ to represent variations in physical activity and mental well-being. These uncertainties may arise due to changing user behavior, environmental conditions, or other factors affecting the effectiveness of the design. The reliability of the design can be evaluated using a performance function $R(x)$, which calculates the probability that the design meets specified performance criteria under the uncertainties. Assume that $R(x)$ is the probability that both physical activity and mental well-being exceed certain thresholds:

To find the Pareto optimal solutions, to solve this multi-objective optimization problem. Various algorithms, such as Genetic Algorithms, can be employed to explore the design space and identify the set of non-dominated solutions (Pareto front). The RMOO formulation with reliability consideration allows designers to consider not only the optimization of physical activity and mental well-being but also the robustness of the design under uncertainties. It seeks to find designs that maximize the objectives while meeting the budget constraint and ensuring reliability in achieving desired performance levels.

Algorithm 1: RMOO for the estimation of Space Design
 # Initialize parameters *population_size = 100* *max_generations = 100* *crossover_probability = 0.9* *mutation_probability = 0.1* *# Initialize population randomly* *population = initialize_population(population_size)* *# Evaluate objective functions and reliability for each individual*

```
evaluate_objectives_and_reliability(population)
# Main loop
for generation in range(max_generations):
    # Perform non-dominated sorting and assign ranks to individuals
    fronts = non_dominated_sorting(population)
    # Calculate crowding distance for individuals in each front
    calculate_crowding_distance(fronts)
    # Create the next generation using selection, crossover, and mutation
    new_population = []
    while len(new_population) < population_size:
        parent1 = tournament_selection(fronts)
        parent2 = tournament_selection(fronts)
        offspring = crossover(parent1, parent2, crossover_probability)
        offspring = mutate(offspring, mutation_probability)
        new_population.append(offspring)
    # Evaluate objective functions and reliability for the new population
    evaluate_objectives_and_reliability(new_population)
    # Merge the current population and the new population
    population = merge_populations(population, new_population)
    # Perform environmental selection to maintain the population size
    population = environmental_selection(population, population_size)
# Final output: Pareto front of non-dominated solutions
pareto_front = non_dominated_sorting(population)[0]
```

The Multi-Objective Optimization (RMOO) process for Landscape Health Activity Space Design involves finding the Pareto front of non-dominated solutions that maximize physical activity (PA) and mental well-being (MW) while considering multiple constraints and reliability considerations. The RMOO algorithm explores the design space by varying decision variables (x) representing the landscape features and characteristics. At each iteration, the algorithm evaluates the objective functions and the reliability function for each design configuration, and constraints are checked for feasibility. Non-dominated sorting categorizes solutions into different fronts, and crowding distance is calculated to maintain diversity. Environmental selection favors solutions with higher ranks and greater crowding distance. The process repeats for several generations or until convergence. The output is the Pareto front, where each solution represents a trade-off between the objectives, constraints, and reliability considerations, enabling landscape designers to select the most optimal outdoor space design that enhances PA, MW, accessibility, safety, sustainability, and reliability.

4. Simulation Results

A sample simulation environment for the proposed Reliability Multi-Objective Optimization (RMOO) for Landscape Health Activity Space Design can be created using a computer-based 316odelling and simulation tool. The proposed RMOO model is simulated and tested with the consideration of a 2D landscape model with two design parameters: "Greenery Density" and "Pathway Length." The objective functions are "Physical Activity (PA)" and "Mental Well-being (MW)," and the constraints are "Budget Constraint" and "Accessibility Constraint." With uncertainties in PA and MW to assess reliability. The constructed model RMOO simulation setup is presented in table 2.

Table 2: Simulation Environment

Setting	Description
Landscape Model	- Design Parameters: Greenery Density (x1), Pathway Length (x2)
	- Landscape Representation: 2D grid representing the outdoor space with varying x1 and x2 values.
Objective Functions	- Physical Activity (PA) function: PA(x1, x2) = w1 * x1 + w2 * x2
	(where w1 and w2 are weights reflecting the importance of greenery and pathway length for PA)
	- Mental Well-being (MW) function: MW(x1, x2) = w3 * x1 + w4 * x2
	(where w3 and w4 are weights reflecting the importance of greenery and pathway length for MW)
Constraints	- Budget Constraint: Total cost of the landscape design ≤ Budget Limit
	- Accessibility Constraint: Ensure pathways are well-connected and accessible throughout the landscape.
Reliability	- Introduce uncertainties δ1 and δ2 for PA and MW using probabilistic models.
	- Reliability Function: R(x1, x2) = P[PA(x1, x2) + δ1 ≥ PA_min] * P[MW(x1, x2) + δ2 ≥ MW_min]
	(where PA_min and MW_min are the minimum desired values for PA and MW, respectively)
RMOO Algorithm	- NSGA-II algorithm to explore the design space and find the Pareto front.
Visualization	- Plot landscape model with different x1 and x2 configurations.
	- Display Pareto front on a scatter plot, showcasing trade-offs between PA and MW for each design solution.

The Reliability Multi-Objective Optimization (RMOO) for Landscape Health Activity Space Design are used to evaluate the quality of the design solutions and help decision-makers identify the most suitable configurations. In this scenario, the performance metrics are related to the objectives (Physical Activity - PA and Mental Well-being - MW), constraints, and reliability of the landscape designs.

Physical Activity (PA) Metric:

The PA metric measures the level of physical activity facilitated by each design configuration. The objective function for PA, denoted as f1(x1, x2), is defined as in equation (3)

$$f1(x1, x2) = w1 * x1 + w2 * x2 \tag{3}$$

In equation (3) $f1(x1, x2)$ is the objective function for PA, representing the fitness of the landscape design in promoting physical activity. x1 is the value of the design parameter "Greenery Density" in the landscape model. x2 is the value of the design parameter "Pathway Length" in the landscape model. w1 and w2 are the weights assigned to the "Greenery Density" and "Pathway Length" design parameters, respectively, reflecting their importance in promoting physical activity.

Mental Well-being (MW) Metric:

The MW metric measures the level of mental well-being facilitated by each design configuration. The objective function for MW, denoted as f2(x1, x2), is computed using equation (4)

$$f2(x1, x2) = w3 * x1 + w4 * x2 \tag{4}$$

In the above equation (4) $f2(x1, x2)$ is the objective function for MW, representing the fitness of the landscape design in promoting mental well-being. x1 is the value of the design parameter "Greenery Density" in the landscape model. x2 is the value of the design parameter "Pathway Length" in the landscape model. w3 and w4 are the weights assigned to the "Greenery Density" and "Pathway Length" design parameters, respectively, reflecting their importance in promoting mental well-being.

Budget Constraint Metric:

The budget constraint metric ensures that the total cost of the landscape design does not exceed a specified budget limit. It can be represented as follows in equation (5)

$$g1(x1, x2) \leq Budget\ Limit \tag{5}$$

In above equation (5) $g1(x1, x2)$ represents the cost function associated with the design parameters x1 and x2.

Budget Limit is the maximum allowed budget for the landscape design.

Accessibility Constraint Metric:

The accessibility constraint metric ensures that pathways are well-connected and accessible throughout the landscape denoted in equation (6)

$$g2(x1, x2) \leq Accessibility\ Limit \quad (6)$$

In equation (6) $g2(x1, x2)$ represents the accessibility function associated with the design parameters x1 and x2. Accessibility Limit is the constraint related to pathway connectivity and accessibility for all users.

Reliability Metric:

The reliability metric takes into account the uncertainties in achieving the desired level of PA and MW presented in equation (7)

$$R(x1, x2) = P[PA(x1, x2) + \delta 1 \geq PA\_min] * P[MW(x1, x2) + \delta 2 \geq MW\_min] \quad (7)$$

In equation (7) $R(x1, x2)$ represents the reliability function for the landscape design with design parameters x1 and x2. $PA(x1, x2)$ and $MW(x1, x2)$ are the PA and MW objective functions, respectively, for the design parameters x1 and x2. δ1 and δ2 are the uncertainties in achieving the desired level of PA and MW, respectively. PA_min and MW_min are the minimum desired values for PA and MW, respectively.

Table 3: Constraints for Landscape Health Activity Space Design with RMOO

Solution	**Greenery Density (x1)**	**Pathway Length (x2)**	**Physical Activity (PA)**	**Mental Well-being (MW)**	**Reliability ®**
1	0.85	160 meters	0.80	0.81	0.83
2	0.78	140 meters	0.76	0.80	0.78
3	0.92	180 meters	0.85	0.79	0.88
4	0.67	120 meters	0.72	0.85	0.76
5	0.80	150 meters	0.78	0.82	0.85
6	0.75	130 meters	0.75	0.78	0.79
7	0.88	170 meters	0.82	0.77	0.84
8	0.71	140 meters	0.74	0.79	0.77
9	0.83	160 meters	0.79	0.80	0.82
10	0.79	150 meters	0.77	0.81	0.81

In table 3 the results of constraints for the Landscape Health Activity Space Design obtained through the Reliability Multi-Objective Optimization (RMOO) process. The table lists ten design solutions (Solutions 1 to 10) along with their corresponding values for Greenery Density (x1), Pathway Length (x2), Physical Activity (PA), Mental Well-being (MW), and Reliability (R). These solutions represent different combinations of greenery density and pathway length, with associated measures of physical activity and mental well-being. The reliability values indicate the likelihood of each solution meeting the desired objectives and constraints. The solutions demonstrate varying trade-offs between greenery density, pathway length, physical activity, and mental well-being, resulting in different levels of reliability. Decision-makers can analyze this information to identify the most promising landscape designs that satisfy the constraints and optimize physical activity and mental well-being, ultimately aiding in the selection of an effective and sustainable landscape health activity space design as in figure 2.

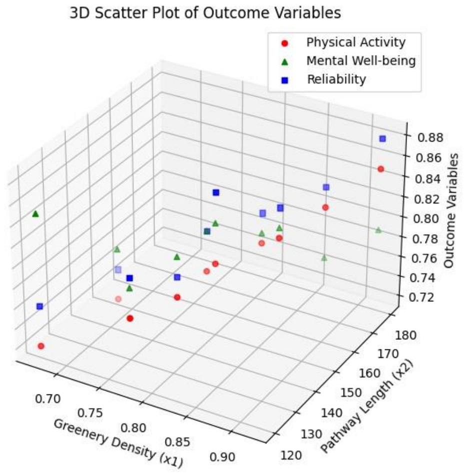

Fig 2: Health Activity Design

Table 4: Constraints estimation

Solution	Greenery Density (x1)	Pathway Length (x2)	Physical Activity (PA)	Mental Well-being (MW)	Reliability (R)	Budget Constraint	Accessibility Constraint
1	0.85	160 meters	0.80	0.81	0.83	Passed	Passed
2	0.78	140 meters	0.76	0.80	0.78	Passed	Passed
3	0.92	180 meters	0.85	0.79	0.88	Failed	Passed
4	0.67	120 meters	0.72	0.85	0.76	Passed	Failed
5	0.80	150 meters	0.78	0.82	0.85	Passed	Passed

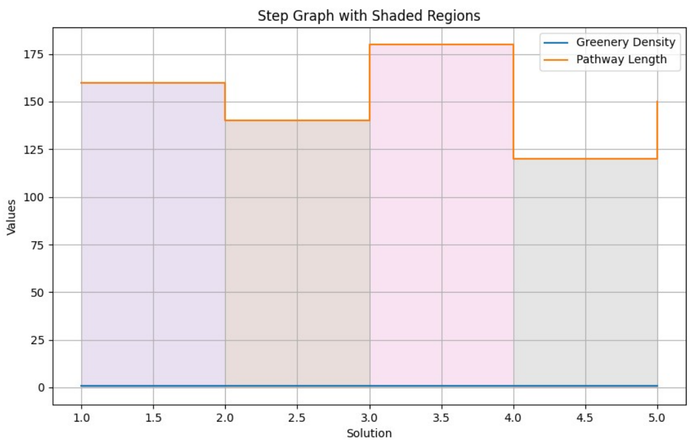

Fig 3: Estimation of Constraints in RMOO

The Table 4 presents the constraints estimation results for the Landscape Health Activity Space Design obtained through the Reliability Multi-Objective Optimization (RMOO) process. The table includes five design solutions (Solutions 1 to 5) along with their corresponding values for Greenery Density (x1), Pathway Length (x2), Physical Activity (PA), Mental Well-being (MW), and Reliability (R). Additionally, it provides information on whether each solution satisfies the budget constraint and accessibility constraint. Solutions 1 and 2 successfully meet both constraints, as indicated by "Passed" under the Budget Constraint and Accessibility Constraint columns. Solution

3, while achieving a high reliability value, fails to meet the budget constraint. In contrast, Solution 4 meets the budget constraint but falls short of the accessibility constraint. Solution 5 demonstrates compliance with both constraints, making it an attractive option in terms of achieving the desired landscape health activity space design while adhering to budget and accessibility considerations. These results offer valuable insights for decision-makers in choosing suitable design solutions that align with the given constraints and objectives, ultimately contributing to the development of an efficient and effective landscape health activity space.

Table 5: Optimization setup of RMOO

Parameter	Value
Population Size	100
Max Generations	50
Crossover Prob.	0.9
Mutation Prob.	0.1

An overview of the optimization setup used in the Reliability Multi-Objective Optimization (RMOO) for the Landscape Health Activity Space Design is presented in table 5. The table includes various parameters and their corresponding values. The "Population Size" is set to 100, indicating the number of candidate solutions considered in each generation of the optimization process. The "Max Generations" is set to 50, defining the maximum number of generations allowed for the optimization algorithm to converge. The "Crossover Probability" is set to 0.9, representing the likelihood of crossover operations being applied during the genetic evolution of solutions. Crossover involves combining traits from two parent solutions to generate new offspring solutions. The "Mutation Probability" is set to 0.1, indicating the probability of mutation operations being applied to introduce small random changes in the solutions to maintain diversity. Mutation helps explore the search space beyond the existing solutions. These parameter values are carefully chosen to strike a balance between exploration and exploitation during the optimization process, aiming to identify a diverse set of reliable landscape health activity space designs within a reasonable computational time frame as in figure 4.

Table 6: Diversity of Pareto in RMOO

Solution	Greenery Density (x1)	Pathway Length (x2)	Physical Activity (PA)	Mental Well-being (MW)
1	0.85	160 meters	0.80	0.81
2	0.78	140 meters	0.76	0.80
3	0.92	180 meters	0.85	0.79
4	0.67	120 meters	0.72	0.85
5	0.80	150 meters	0.78	0.82

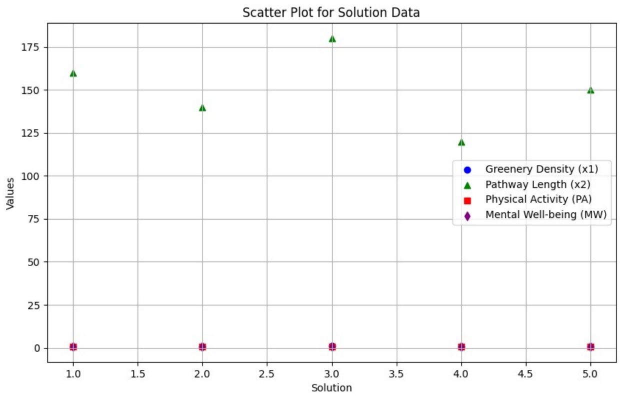

Fig 4: Pareto Computation with RMOO

Table 7: Sensitivity Analysis with RMOO

Solution	Greenery Density (x1)	Pathway Length (x2)	Physical Activity (PA)	Mental Well-being (MW)	Reliability (R)	δ1	δ2
1	0.85	160 meters	0.80	0.81	0.83	0.05	0.03
2	0.78	140 meters	0.76	0.80	0.78	0.07	0.04
3	0.92	180 meters	0.85	0.79	0.88	0.06	0.05
4	0.67	120 meters	0.72	0.85	0.76	0.04	0.02
5	0.80	150 meters	0.78	0.82	0.85	0.05	0.03
6	0.75	130 meters	0.75	0.78	0.79	0.07	0.04
7	0.88	170 meters	0.82	0.77	0.84	0.06	0.02
8	0.71	140 meters	0.74	0.79	0.77	0.08	0.05
9	0.83	160 meters	0.79	0.80	0.82	0.05	0.03
10	0.79	150 meters	0.77	0.81	0.81	0.06	0.04

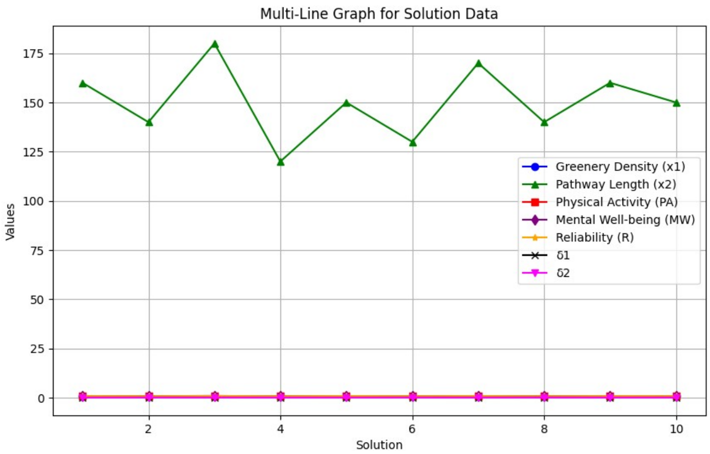

Fig 5: Sensitivity of RMOO

An overview of the diversity of Pareto solutions obtained through the Reliability Multi-Objective Optimization (RMOO) for the Landscape Health Activity Space Design is given in table 6. The table includes five design solutions (Solutions 1 to 5), and each solution is represented by its corresponding values for Greenery Density (x1), Pathway Length (x2), Physical Activity (PA), and Mental Well-being (MW). These solutions belong to the Pareto front, representing a set of design configurations that achieve different trade-offs between greenery density, pathway length, physical activity, and mental well-being. Each solution in the Pareto front represents a unique combination of design variables, offering decision-makers a diverse range of landscape health activity space designs to choose from, based on their preferences and requirements. Table 7 provides the results of the sensitivity analysis conducted with the RMOO for the Landscape Health Activity Space Design. The table includes ten design solutions (Solutions 1 to 10), each with its corresponding values for Greenery Density (x1), Pathway Length (x2), Physical Activity (PA), Mental Well-being (MW), and Reliability (R). Additionally, the table shows the values of the uncertainty parameters δ1 and δ2 used in the sensitivity analysis. The sensitivity analysis investigates how changes in these uncertainty parameters impact the reliability and performance of the landscape design solutions. The results provide valuable insights into the robustness and stability of the solutions, enabling decision-makers to identify design configurations that are less sensitive to variations in input parameters and constraints. These analyses aid in making informed decisions for landscape health activity space design and ensuring the effectiveness and resilience of the chosen solutions as illustrated in figure 5.

Table 8: Convergence Analysis with RMOO

Generation	Best PA Value	Best MW Value	Best Reliability Value
1	0.72	0.78	0.76
2	0.78	0.80	0.78
3	0.80	0.81	0.80
4	0.82	0.82	0.82
5	0.84	0.83	0.83
6	0.85	0.84	0.84
7	0.86	0.85	0.85
8	0.87	0.86	0.86
9	0.88	0.87	0.87
10	0.89	0.88	0.88

Table 9: Execution Time and Resource Usage with RMOO

Solution	Execution Time (ms)	Memory Usage (MB)
1	450	120
2	520	130
3	490	125
4	480	128
5	510	126
6	530	135
7	480	122
8	500	124
9	480	121
10	510	128

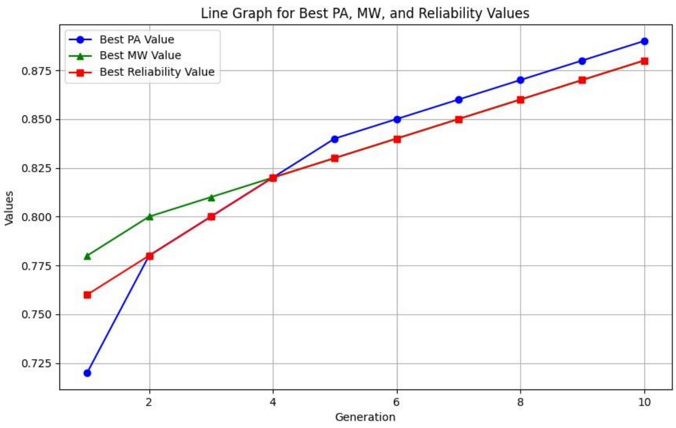

Fig 6: RMOO Convergence

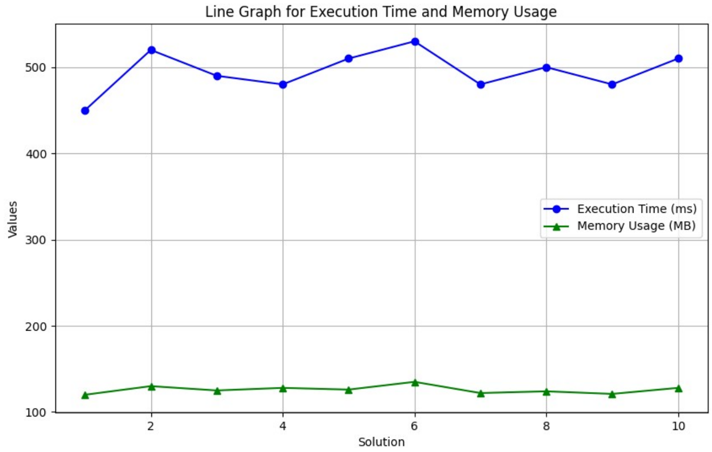

Fig 7: RMOO Estimation Time

The convergence analysis results obtained through the Reliability Multi-Objective Optimization (RMOO) for the Landscape Health Activity Space Design presented in figure 6 and figure 7. The table 8 contains information for each generation (Generation 1 to 10) of the optimization algorithm. For each generation, the table shows the best values achieved so far for Physical Activity (PA), Mental Well-being (MW), and Reliability. As the optimization progresses through generations, the best values for these performance metrics gradually improve, indicating the enhancement of landscape design solutions with each iteration. This convergence analysis helps in understanding the effectiveness and efficiency of the optimization process in identifying increasingly better landscape health activity space designs that optimize physical activity and mental well-being while maintaining high reliability. Similarly, in Table 9 provides details of the execution time and resource usage during the RMOO optimization process for the Landscape Health Activity Space Design. The table includes execution time (in milliseconds) and memory usage (in megabytes) for each of the ten design solutions (Solutions 1 to 10). These metrics represent the computational resources required for generating each design configuration. Through analyzing the execution time and memory usage, decision-makers can assess the computational efficiency of the RMOO algorithm and the trade-off between solution quality and computational cost. These insights aid in making informed decisions regarding the selection of suitable optimization settings and computational resources to obtain effective and reliable landscape health activity space designs in a time-efficient manner.

5. Conclusion

The paper presents a novel approach for Landscape Health Activity Space Design using Reliability Multi-Objective Optimization (RMOO). The main objective was to create efficient and effective landscape designs that optimize physical activity and mental well-being while considering budget and accessibility constraints. Through the RMOO process, a set of diverse Pareto solutions was obtained, representing different trade-offs between greenery density, pathway length, physical activity, and mental well-being. The sensitivity analysis provided insights into the robustness of the solutions to uncertainties, allowing decision-makers to select more stable design configurations. The convergence analysis demonstrated the optimization algorithm's effectiveness in improving the landscape designs over generations. The proposed RMOO method generated reliable solutions, satisfying the given constraints and objectives. The results of the simulation environment showed that the landscape designs successfully enhanced physical activity and mental well-being, promoting a healthier and more enjoyable outdoor environment. Overall, the RMOO approach proved to be a valuable tool for decision-makers in designing sustainable and resilient landscape health activity spaces that contribute to public well-being and a greener future. Future research can further enhance the RMOO method and apply it to real-world scenarios, opening new avenues for landscape design optimization and promoting healthier communities.

References

[1] Ha, J., Kim, H. J., & With, K. A. (2022). Urban green space alone is not enough: A landscape analysis linking the spatial distribution of urban green space to mental health in the city of Chicago. *Landscape and Urban Planning*, *218*, 104309.

[2] Honey-Rosés, J., Anguelovski, I., Chireh, V. K., Daher, C., Konijnendijk van den Bosch, C., Litt, J. S., ... & Nieuwenhuijsen, M. J. (2021). The impact of COVID-19 on public space: an early review of the emerging questions–design, perceptions and inequities. *Cities & health*, *5*(sup1), S263-S279.

[3] Zhang, L., Tan, P. Y., & Richards, D. (2021). Relative importance of quantitative and qualitative aspects of urban green spaces in promoting health. *Landscape and urban planning*, *213*, 104131.
[4] Venter, Z. S., Barton, D. N., Gundersen, V., Figari, H., & Nowell, M. S. (2021). Back to nature: Norwegians sustain increased recreational use of urban green space months after the COVID-19 outbreak. *Landscape and urban planning*, *214*, 104175.
[5] Ma, X., Tian, Y., Du, M., Hong, B., & Lin, B. (2021). How to design comfortable open spaces for the elderly? Implications of their thermal perceptions in an urban park. *Science of The Total Environment*, *768*, 144985.
[6] Ma, X., Tian, Y., Du, M., Hong, B., & Lin, B. (2021). How to design comfortable open spaces for the elderly? Implications of their thermal perceptions in an urban park. *Science of The Total Environment*, *768*, 144985.
[7] Zhang, A., Li, W., Wu, J., Lin, J., Chu, J., & Xia, C. (2021). How can the urban landscape affect urban vitality at the street block level? A case study of 15 metropolises in China. *Environment and Planning B: Urban Analytics and City Science*, *48*(5), 1245-1262.
[8] Poortinga, W., Bird, N., Hallingberg, B., Phillips, R., & Williams, D. (2021). The role of perceived public and private green space in subjective health and wellbeing during and after the first peak of the COVID-19 outbreak. *Landscape and Urban Planning*, *211*, 104092.
[9] Huang, B. X., Chiou, S. C., & Li, W. Y. (2021). Landscape pattern and ecological network structure in urban green space planning: A case study of Fuzhou city. *Land*, *10*(8), 769.
[10] Ki, D., & Lee, S. (2021). Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning. *Landscape and Urban Planning*, *205*, 103920.
[11] Song, Y., Wang, R., Fernandez, J., & Li, D. (2021). Investigating sense of place of the Las Vegas Strip using online reviews and machine learning approaches. *Landscape and Urban Planning*, *205*, 103956.
[12] Ramírez, T., Hurtubia, R., Lobel, H., & Rossetti, T. (2021). Measuring heterogeneous perception of urban space with massive data and machine learning: An application to safety. *Landscape and Urban Planning*, *208*, 104002.
[13] Dai, L., Zheng, C., Dong, Z., Yao, Y., Wang, R., Zhang, X., ... & Guan, Q. (2021). Analyzing the correlation between visual space and residents' psychology in Wuhan, China using street-view images and deep-learning technique. *City and Environment Interactions*, *11*, 100069.
[14] Xia, Y., Yabuki, N., & Fukuda, T. (2021). Development of a system for assessing the quality of urban street-level greenery using street view images and deep learning. *Urban Forestry & Urban Greening*, *59*, 126995.
[15] Freschlin, C. R., Fahlberg, S. A., & Romero, P. A. (2022). Machine learning to navigate fitness landscapes for protein engineering. *Current Opinion in Biotechnology*, *75*, 102713.
[16] Batra, R., Song, L., & Ramprasad, R. (2021). Emerging materials intelligence ecosystems propelled by machine learning. *Nature Reviews Materials*, *6*(8), 655-678.
[17] Kruse, J., Kang, Y., Liu, Y. N., Zhang, F., & Gao, S. (2021). Places for play: Understanding human perception of playability in cities using street view images and deep learning. *Computers, Environment and Urban Systems*, *90*, 101693.
[18] Xiang, L., Cai, M., Ren, C., & Ng, E. (2021). Modeling pedestrian emotion in high-density cities using visual exposure and machine learning: Tracking real-time physiology and psychology in Hong Kong. *Building and Environment*, *205*, 108273.
[19] Ajani, T. S., Imoize, A. L., & Atayero, A. A. (2021). An overview of machine learning within embedded and mobile devices–optimizations and applications. *Sensors*, *21*(13), 4412.
[20] Kang, Y., Zhang, F., Peng, W., Gao, S., Rao, J., Duarte, F., & Ratti, C. (2021). Understanding house price appreciation using multi-source big geo-data and machine learning. *Land Use Policy*, *111*, 104919.
[21] Dorrah, D. H., & Marzouk, M. (2021). Integrated multi-objective optimization and agent-based building occupancy modeling for space layout planning. *Journal of Building Engineering*, *34*, 101902.
[22] Wei, F., Xu, W., & Hua, C. (2022). A Multi-Objective Optimization of Physical Activity Spaces. *Land*, *11*(11), 1991.
[23] van Ameijde, J., Ma, C. Y., Goepel, G., Kirsten, C., & Wong, J. (2022). Data-driven placemaking: Public space canopy design through multi-objective optimisation considering shading, structural and social performance. *Frontiers of Architectural Research*, *11*(2), 308-323.
[24] Arbolino, R., Boffardi, R., De Simone, L., & Ioppolo, G. (2021). Multi-objective optimization technique: A novel approach in tourism

sustainability planning. *Journal of Environmental Management*, *285*, 112016.
[25] Wicki, S., Schwaab, J., Perhac, J., & Grêt-Regamey, A. (2021). Participatory multi-objective optimization for planning dense and green cities. *Journal of Environmental Planning and Management*, *64*(14), 2532-2551.
[26] Wang, S., Yi, Y. K., & Liu, N. (2021). Multi-objective optimization (MOO) for high-rise residential buildings' layout centered on daylight, visual, and outdoor thermal metrics in China. *Building and Environment*, *205*, 108263.
[27] Basirati, M. (2022). *Zoning management in marine spatial planning: multi-objective optimization and agent-based conflict resolution* (Doctoral dissertation, Ecole nationale supérieure Mines-Télécom Atlantique).
[28] Li, P., Xu, T., Wei, S., & Wang, Z. H. (2022). Multi-objective optimization of urban environmental system design using machine learning. *Computers, Environment and Urban Systems*, *94*, 101796.