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RESEARCH

Optimizing urban walkability with NSGA-III for sustainable city planning and construction

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Abstract
Urban walkability is essential for sustainable city planning and construction, fostering public health, environmental benefits, and social equity. However, optimizing walkability involves balancing multiple, often conflicting objectives, such as accessibility, safety, environmental quality, and social inclusivity. This paper presents a novel approach to optimizing urban walkability using the Non-dominated Sorting Genetic Algorithm III (NSGA-III). By applying NSGA-III, we address the complexities of multi-objective optimization in urban environments, generating a set of Pareto-optimal solutions that cater to diverse planning priorities. A case study in a mid-sized urban area demonstrates the effectiveness of the proposed methodology. The results highlight key trade-offs between objectives, such as the balance between accessibility and safety or environmental quality and social inclusivity. The findings provide urban planners with a robust decision-making framework that supports the creation of walkable, sustainable cities. The study concludes with policy recommendations to enhance urban walkability and suggests avenues for future research, including the integration of economic considerations and the application of this approach in larger, more complex urban settings. This research contributes to the field of urban planning by offering a comprehensive tool for optimizing walkability, ultimately promoting more livable and sustainable cities.

Keywords Urban Walkability · Sustainable City Planning · Multi-Objective Optimization · NSGA-III · Pareto-Optimal Solutions

Introduction

Urban walkability, a key component of sustainable city planning, plays a vital role in enhancing the quality of life in urban environments (Kaveh and Laknejadi 2011a). It promotes healthier lifestyles by encouraging physical activity, reduces traffic congestion, and lowers greenhouse gas emissions, contributing to overall environmental sustainability (Kaveh, Laknejadi, and Alinejad 2012). Moreover, walkable cities foster stronger social connections and economic vitality by making public spaces more accessible and engaging for residents and visitors alike (Agarwal et al. 2024; Arya et al. 2024). As cities around the world strive to become more sustainable, optimizing walkability has emerged as a crucial goal for urban planners.

However, the optimization of urban walkability is a complex, multi-dimensional problem that requires balancing a variety of conflicting objectives (Sethi, Prajapati, et al. 2024; Sharma and Sharma 2024). For instance, improving accessibility to services and amenities often necessitates increased urban density, which can lead to higher levels of pollution and reduced green space (Sethi, Rathinakumar, et al. 2024). Similarly, enhancing pedestrian safety might require extensive infrastructure investments, which could be at odds with budgetary constraints and existing urban layouts (Sharma and Trivedi 2021; Trivedi and Sharma 2023). Traditional urban planning methods often struggle to address these complexities, as they tend to focus on single-objective solutions that do not account for the intricate trade-offs inherent in walkability (Agarwal 2024).

To address these challenges, advanced multi-objective optimization techniques are increasingly being employed in urban planning. Among these, the Non-dominated Sorting Genetic Algorithm III (NSGA-III) has gained prominence

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due to its ability to handle high-dimensional objective spaces effectively (Deb and Jain 2013). NSGA-III improves upon earlier algorithms by efficiently generating a diverse set of Pareto-optimal solutions, which are critical for decision-makers who need to consider multiple criteria simultaneously. This makes NSGA-III particularly well-suited for optimizing urba walkability, where diverse and often conflicting objectives must be balanced (Sharma and Trivedi 2022b, 2023, b).

This paper aims to explore the application of NSGA-III in optimizing urban walkability, focusing on four key objectives: accessibility, safety, environmental quality, and social inclusivity. By applying NSGA-III to a mid-sized urban area, we seek to demonstrate how this algorithm can generate practical solutions that support sustainable city planning. The results of this study not only highlight the effectiveness of NSGA-III in managing complex trade-offs but also provide urban planners with actionable insights that can guide the development of more walkable and livable cities. The remainder of this paper is organized as follows: The literature review provides an overview of previous studies on urban walkability and multi-objective optimization in urban planning. The research methodology details the step-by-step process of applying NSGA-III to the problem of walkability optimization. The results section presents the outcomes of the optimization process, followed by a discussion of the findings and their implications for urban planning. Finally, the paper concludes with policy recommendations and suggestions for future research.

Literature review

Urban walkability has been a focal point of research in urban planning, public health, and environmental studies due to its multifaceted impact on cities and their inhabitants (Patil et al. 2024; Sharma and Trivedi 2023, a). Walkability is generally defined as the extent to which the built environment encourages walking by providing safe, comfortable, and accessible pedestrian pathways that connect people to various destinations (Sharma and Trivedi 2022a, 2023, c). Studies have consistently shown that walkable environments contribute to public health by encouraging physical activity, which in turn reduces the incidence of chronic diseases such as obesity, diabetes, and cardiovascular conditions (Kaveh and Bakhshpoori 2016; Kaveh and Laknejadi 2013). Additionally, walkable cities are associated with lower levels of pollution and greenhouse gas emissions, as they reduce the dependency on automobiles, leading to fewer vehicle miles traveled and less air pollution (Kaveh, Dadras, and Malek 2018; Kaveh and Laknejadi 2011b).

The relationship between walkability and urban sustainability has also been widely documented (Mohamad Karimi et al. 2007). Sustainable urban development emphasizes the need for integrated land use and transportation planning that promotes compact, mixed-use neighborhoods (Ma et al. 2012). These neighborhoods typically feature a dense network of walkable streets that not only reduce the need for motorized transportation but also support local economies by increasing foot traffic to businesses (Asadi et al. 2014). Moreover, walkability is linked to social sustainability, as it enhances social interactions and community cohesion by encouraging people to spend more time in public spaces (Son and Kim 2016). However, achieving high levels of walkability in urban areas is challenging, as it requires a careful balance of factors such as density, land use mix, connectivity, safety, and accessibility (Asadi et al. 2012; Nusen et al. 2021).

Multi-objective optimization has become a crucial tool in addressing the complexities of urban planning, particularly in the context of walkability (Rastegar Moghaddam, Khanzadi, and Kaveh 2021). Traditional planning approaches often focus on single objectives, such as minimizing travel time or maximizing land use efficiency, which can lead to suboptimal outcomes when other important factors are overlooked (Antipova et al. 2014; Manjarres et al. 2019). In contrast, multi-objective optimization allows planners to consider and balance multiple objectives simultaneously, leading to more holistic and sustainable urban designs. Algorithms such as NSGA-II and NSGA-III have been widely used in various urban planning applications, including transportation planning, land use allocation, and environmental management (Deb et al. 2002; Jain and Deb 2014).

The Non-dominated Sorting Genetic Algorithm III (NSGA-III) represents a significant advancement in multi-objective optimization, particularly in scenarios involving many objectives (Kaveh, Izadifard, and Mottaghi 2020; Kaveh and Rajabi 2022). Unlike its predecessors, NSGA-III is specifically designed to handle high-dimensional objective spaces, making it well-suited for complex urban planning problems where multiple, often conflicting, criteria must be optimized (Deb and Jain 2013). NSGA-III has been successfully applied in various fields, including engineering design, environmental management, and logistics, but its application in urban walkability optimization is relatively recent (Kaveh, Fahimi-Farzam, and Kalateh-Ahani 2015). Studies using NSGA-III have demonstrated its effectiveness in generating diverse sets of Pareto-optimal solutions, providing urban planners with a range of viable options that reflect different trade-offs between objectives (Kaveh, Kalateh-Ahani, and Fahimi-Farzam 2013; Kaveh, Moghanni, and Javadi 2019).

Recent research has begun to explore the application of NSGA-III to urban walkability, with promising results (Elazouni 2009; Uzir et al. 2020). For example, studies have used NSGA-III to optimize the placement of pedestrian infrastructure, the design of mixed-use neighborhoods, and the allocation of green spaces, all while balancing objectives such as safety, accessibility, and environmental quality (Benbouzid-SiTayeb et al. 2019; Lèbre, Corder, and Golev 2017). These studies highlight the potential of NSGA-III to enhance walkability by enabling planners to consider a wide array of factors and to generate solutions that are both efficient and equitable. However, there is still a need for further research to refine these methods and to explore their application in different urban contexts, particularly in large, densely populated cities where the challenges of walkability are most pronounced.

In conclusion, the literature underscores the importance of walkability for urban sustainability and the potential of multi-objective optimization, particularly NSGA-III, in addressing the complexities of urban planning. While significant progress has been made, ongoing research is essential to fully realize the benefits of these approaches and to develop practical tools that can be widely adopted by urban planners. This study aims to contribute to this growing body of knowledge by applying NSGA-III to the optimization of urban walkability, with a focus on balancing accessibility, safety, environmental quality, and social inclusivity.

Research methodology

Objective functions for optimizing urban walkability

In the context of optimizing urban walkability, four key objective functions are defined in this study. Each objective function represents a different dimension of walkability, which needs to be optimized simultaneously. The goal is to find solutions that balance these objectives to create a sustainable and walkable urban environment. These four objectives are formulated as follows;

Objective 1: Accessibility (O1) (Maximize accessibility to essential services and amenities)

This objective minimizes the average distance between residential areas and essential services. This ensures that residents have easy access to key amenities, contributing to a walkable city. Mathematical formulation of this objective is represented as Eq. (1).

$$Maximize\ O_1 = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{d_i} \tag{1}$$

Where, N is the total number of essential services (e.g., public transport, schools, healthcare facilities), and d_i is the distance from a given residential area to the service i.

Objective 2: Safety (O2) (Minimize pedestrian accidents and enhance safety features)

This objective seeks to reduce the accident rate by improving safety features in pedestrian zones. The inverse relationship with safety infrastructure indicates that better safety features lead to fewer accidents. Mathematical formulation of this objective is represented as Eq. (2).

$$Minimize\ O_2 = \frac{1}{M}\sum_{i=1}^{M}\left(A_j + \frac{1}{L_j}\right) \tag{2}$$

Where, M is the total number of pedestrian zones or intersections, A_j represents the accident rate in zone j, and L_j represents the level of safety infrastructure (e.g., crosswalks, lighting) in zone j.

Objective 3: Environmental quality (O3) (Minimize pollution levels and maximize green spaces)

This objective aims to enhance environmental quality by increasing green spaces and reducing pollution. A higher ratio of green spaces to pollution levels indicates a better quality of life for pedestrians. Mathematical formulation of this objective is represented as Eq. (3).

$$Minimize\ O_3 = \frac{G}{P} \tag{3}$$

Where, G is the total area of green spaces within the urban environment, and P is the pollution index, measured by factors such as air and noise pollution levels.

Objective 4: Social inclusivity (O4) (Maximize inclusivity for all demographic groups)

This objective ensures that the urban environment is accessible to all demographic groups. By maximizing the inclusivity score relative to the population of each group, the city can be made walkable for everyone, regardless of age or physical ability. Mathematical formulation of this objective is represented as Eq. (4).

$$Maximize\ O_4 = \frac{1}{K}\sum_{k=1}^{K}\frac{S_k}{N_k} \tag{4}$$

Where, K is the total number of demographic groups (e.g., elderly, disabled), S_k is the score of inclusivity measures (e.g., ramps, wide sidewalks) for group k, and N_k is the population of group k.

Combined objective function for multi-objective optimization

In a multi-objective optimization framework like NSGA-III, these individual objective functions are optimized simultaneously. The algorithm seeks to find a set of solutions where no single objective can be improved without worsening at least one other objective, resulting in a Pareto-optimal set of solutions. Mathematically, the combined objectives are represented as Eq. (5).

$$Optimize\ O = \{O_1,\ O_2, O_3, O_4\} \tag{5}$$

These objective functions are designed to capture the essential aspects of urban walkability, balancing the need for accessibility, safety, environmental quality, and social inclusivity. By optimizing these functions using NSGA-III, urban planners can identify solutions that contribute to the creation of walkable, sustainable cities.

Data collection

To optimize urban walkability, a comprehensive dataset is required to accurately represent the different factors influencing walkability. The data collection process focuses on gathering information on accessibility, safety, environmental quality, and social inclusivity across various urban areas. These data are sourced from a combination of public records, geographical information systems (GIS), surveys, and field observations. Table 1 provides an overview of the data sources and variables used in this study, outlining the specific data required for each objective and the corresponding sources from which they were collected.

At this stage, it is required to highlight the detailed description of critical demographic and environmental factors essential for urban planning and decision-making. Population data includes information on total population, age distribution, and density, which are crucial for planning public services and infrastructure development. Housing data covers the types of housing available, such as apartments or single-family homes, along with average occupancy rates, offering insights into housing adequacy and future needs. Employment data provides an understanding of the area's economic health, focusing on employment rates, major industries, and average income levels. Transportation data highlights the modes of transportation commonly used, average commute times, and access to public transit, all of which are vital for optimizing transportation networks and reducing congestion. Environmental data is critical for sustainable urban development, addressing levels of pollution, availability of green spaces, and local climate conditions, all of which contribute to the quality of life. Lastly, social data emphasizes inclusivity by detailing access to essential services for vulnerable groups, ensuring that urban planning efforts are equitable and supportive of all community members. This comprehensive data description equips urban planners and policymakers with the necessary information to make informed decisions that enhance the overall well-being of the urban population.

Data preprocessing and analysis

Before applying the optimization algorithm, the collected data must be preprocessed to ensure consistency and comparability across different variables. The preprocessing steps include data cleaning, handling missing values, normalizing data, and performing initial statistical analyses. Normalization is particularly crucial as it ensures that different variables, which may be measured in different units, are scaled to a common range, allowing for meaningful comparisons. The data normalization process, as illustrated in Fig. 1, involves identifying the range of each variable, rescaling the data to a standard range (typically between 0 and 1), and verifying that the normalization has been applied correctly.

Implementation of NSGA-III

The implementation of the Non-dominated Sorting Genetic Algorithm III (NSGA-III) is a crucial aspect of this study, as it allows for the simultaneous optimization of multiple conflicting objectives related to urban walkability. NSGA-III is particularly well-suited for problems with a large number of objectives, which makes it ideal for urban planning scenarios where factors such as accessibility, safety, environmental quality, and social inclusivity need to be balanced. Below, we detail the step-by-step implementation process, including

Table 1 Overview of data sources and variables

Variable	Description	Data Source
Accessibility (O1)	Distances to essential services such as schools, healthcare, and transport	GIS data, local government databases
Safety (O2)	Pedestrian accident rates, presence of safety infrastructure	Police reports, municipal records
Environmental Quality (O3)	Levels of air and noise pollution, availability of green spaces	Environmental monitoring agencies, GIS
Social Inclusivity (O4)	Accessibility for elderly, disabled, and other vulnerable groups	Surveys, census data, field observations

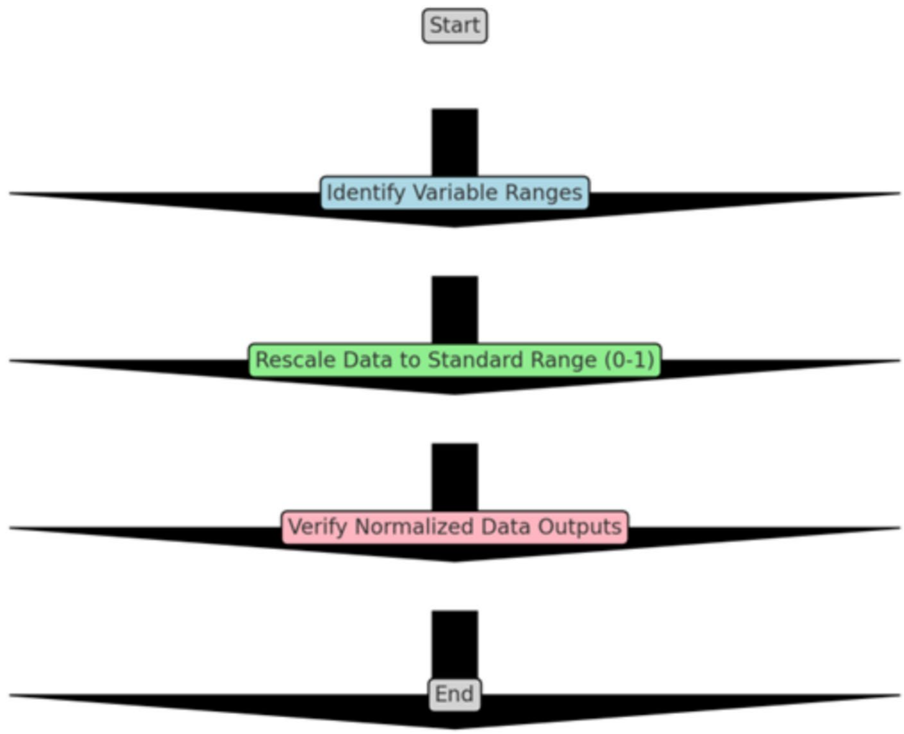

Fig. 1 Data normalization process flowchart

the initialization of the algorithm, the application of genetic operators, the use of non-dominated sorting and reference points, the selection process, and the stopping criteria.

Initialization

The first step in implementing NSGA-III is the initialization of the population of potential solutions. In the context of this study, each solution represents a specific configuration of the urban environment, with assigned values for the objectives of accessibility, safety, environmental quality, and social inclusivity. The population size, which determines the number of solutions to be evolved in each generation, is a critical parameter. A population size of 200 was chosen for this study, balancing the need for computational efficiency with the requirement for a diverse solution set. The initial population is generated randomly within the bounds defined by the decision variables, which correspond to various urban planning factors. This randomness ensures a wide exploration of the solution space from the outset, allowing the algorithm to identify a broad range of potential solutions.

Genetic operators

Once the initial population is generated, NSGA-III employs genetic operators, specifically crossover and mutation, to evolve the population over successive generations. The crossover operator is responsible for combining two parent solutions to produce offspring, promoting the exploration of new regions in the solution space. In this study, a crossover probability of 0.9 was used, meaning that 90% of selected parent pairs undergo crossover. This high probability helps to ensure that the offspring inherit diverse characteristics from their parents, enhancing the algorithm's ability to explore the solution space effectively. Mutation, on the other hand, introduces random changes to individual solutions, thereby maintaining diversity within the population. A mutation probability of 0.1 was applied, ensuring that 10% of the population experiences random modifications each generation. Mutation plays a crucial role in preventing premature convergence to local optima by allowing the algorithm to explore previously unexplored areas of the solution space.

Non-Dominated sorting and reference points

A key feature of NSGA-III is its use of non-dominated sorting and reference points to guide the selection of solutions. Non-dominated sorting is a process where the population is sorted into different fronts based on non-dominance. A solution is non-dominated if no other solution is better in all objectives. The first front consists of the best non-dominated solutions, and subsequent fronts contain solutions that are dominated by those in the previous fronts. This sorting process helps in identifying the most competitive solutions. In addition to non-dominated sorting, NSGA-III uses reference points to maintain diversity among solutions within the same front. These reference points act as targets that the algorithm seeks to approximate with Pareto-optimal solutions. By associating solutions with reference points, NSGA-III ensures that the entire Pareto front is well-represented, even when dealing with high-dimensional objective spaces. This approach is particularly beneficial in urban planning, where multiple objectives must be optimized simultaneously.

Selection and environmental niche preservation

Following the sorting process, NSGA-III selects the next generation of solutions through a process known as environmental niche preservation. This step involves normalizing the solutions and associating them with the closest reference points. The algorithm then selects solutions based on their proximity to these reference points and their contribution to the diversity of the population. Solutions closer to less crowded reference points are favored, ensuring a diverse spread of solutions across the entire objective space. Environmental selection continues until the population size for the next generation is met. If a front cannot be entirely included in the next generation, solutions from that front are selected based on their niche-preserving properties. This process ensures that the final set of solutions is both diverse and representative of the entire Pareto front, providing urban planners with a wide range of viable options.

Stopping criteria

The algorithm iterates through the above steps until a predefined stopping criterion is met. In this study, the stopping criterion is primarily based on the maximum number of generations, which was set at 150. This limit ensures that the algorithm has sufficient time to converge to a stable set of Pareto-optimal solutions without incurring excessive computational costs. In addition to the maximum number of generations, the algorithm also monitors the convergence of the population. If the improvement in the Pareto front is negligible over several generations, the algorithm may terminate early. This early stopping mechanism helps to save computational resources while still ensuring that the final solutions are of high quality.

Final pareto front

The output of the NSGA-III algorithm is a final Pareto front, representing the set of non-dominated solutions that offer the best trade-offs between the objectives. These solutions provide a range of options for urban planners, who can select the most appropriate solution based on specific planning goals, such as maximizing accessibility while minimizing environmental impact. The diversity and spread of the solutions across the Pareto front ensure that planners have a comprehensive set of choices, reflecting the various trade-offs inherent in urban walkability optimization. The flow of the NSGA-III process, including initialization, genetic operations, non-dominated sorting, and niche preservation, is illustrated in the flowchart provided in Fig. 2. This figure outlines the step-by-step implementation of the algorithm, highlighting the interactions between different components and the flow of information through the optimization process.

To ensure the effectiveness of the algorithm, specific parameters are set, as detailed in Table 2. These parameters include the population size, the number of generations, crossover probability, and mutation probability, all of which influence the performance and outcomes of the NSGA-III.

Results and discussion

Analysis of optimization results

The results of the NSGA-III optimization provide a set of Pareto-optimal solutions, each representing a different trade-off between the objectives. These solutions are analyzed to understand the relationships and trade-offs between the

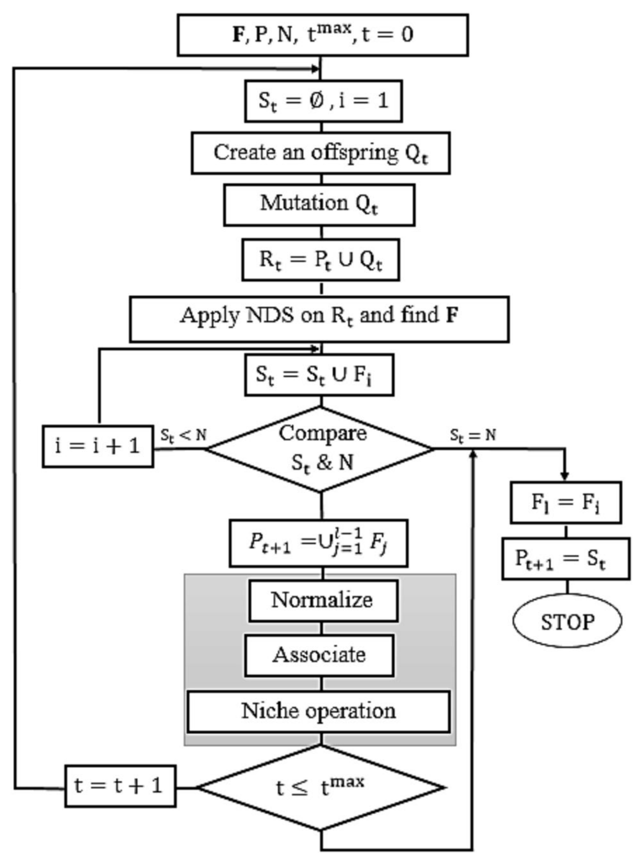

Fig. 2 NSGA-III Algorithm flowchart

Table 2 NSGA-III Parameter settings

Parameter	Value	Description
Population Size	200	The number of solutions in each generation.
Generations	150	The total number of generations for the algorithm to run.
Crossover Probability	0.9	The probability of crossover between pairs of chromosomes.
Mutation Probability	0.1	The probability of mutation in each chromosome.
Reference Points	20 per objective	The number of reference points used for maintaining diversity.

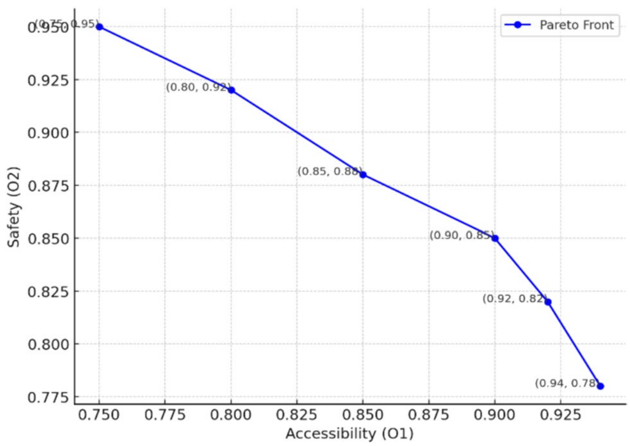

Fig. 3 Example pareto front for accessibility vs. safety

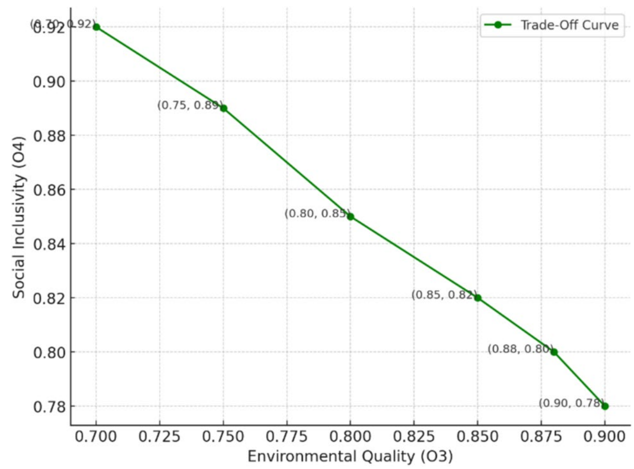

Fig. 4 Trade-Off analysis between environmental quality and social inclusivity

various factors influencing walkability. Figure 3 presents the Pareto front illustrating the trade-off between Accessibility (O1) and Safety (O2) in urban walkability optimization, with each point labeled to show specific values. As accessibility increases from 0.75 to 0.94, safety correspondingly decreases from 0.95 to 0.78, highlighting the inherent trade-offs between these objectives. For instance, the point (0.75, 0.95) offers the highest safety but lowest accessibility, while the point (0.94, 0.78) maximizes accessibility at the cost of reduced safety. This curve allows urban planners to visualize and select solutions that best balance the need for accessible urban environments with the imperative of pedestrian safety, depending on the priorities of their specific planning context.

Further analysis is conducted to examine the trade-off between environmental quality and social inclusivity, as shown in Fig. 4. Figure 4 illustrates the trade-off between Environmental Quality (O3) and Social Inclusivity (O4), where each point on the curve represents a different solution with specific values labeled above the line. As environmental quality improves from 0.70 to 0.90, social inclusivity correspondingly decreases from 0.92 to 0.78. This trend highlights the challenge in urban planning where efforts to enhance green spaces and reduce pollution may result in reduced accessibility and inclusivity for diverse demographic groups. For instance, the point (0.70, 0.92) offers the highest social inclusivity but the lowest environmental quality, while the point (0.90, 0.78) maximizes environmental quality at the cost of social inclusivity. This analysis helps urban planners to understand and balance the trade-offs between creating ecologically sustainable environments and maintaining inclusivity in urban spaces.

Table 3 Summary of selected pareto-optimal solutions

Solution	Accessibility (O1)	Safety (O2)	Environmental Quality (O3)	Social Inclusivity (O4)
S1	0.85	0.78	0.82	0.75
S2	0.8	0.85	0.78	0.8
S3	0.9	0.7	0.85	0.77

Based on the requirements of stakeholders, The Table 3 presents a detailed comparison of selected three Pareto-optimal solutions, each balancing the four key objectives: Accessibility (O1), Safety (O2), Environmental Quality (O3), and Social Inclusivity (O4). Solution S1 offers high accessibility (0.85) and environmental quality (0.82) but at a moderate cost to safety (0.78) and social inclusivity (0.75). This solution might be preferred in scenarios where access to amenities and green spaces are prioritized, even if it means accepting slightly lower safety and inclusivity. Solution S2 provides a more balanced approach, with safety (0.85) and social inclusivity (0.80) being higher, making it ideal for contexts where maintaining a safe and inclusive environment is crucial, albeit with slightly lower accessibility (0.80) and environmental quality (0.78). In contrast, Solution S3 maximizes accessibility (0.90) and environmental quality (0.85), but this comes with significant trade-offs in safety (0.70) and social inclusivity (0.77). This solution would be most suitable for urban planners focused on maximizing access and environmental improvements, even at the expense of lower safety and inclusivity. The trade-offs illustrated in this table provide critical insights for urban planners, enabling them to select the solution that best aligns with their specific priorities and the needs of the community they serve.

Validation and sensitivity analysis

As shown in Table 4, the validation and sensitivity analysis play a crucial role in ensuring the robustness of the optimization results by examining how variations in the parameters of each objective function—Accessibility (O1), Safety (O2), Environmental Quality (O3), and Social Inclusivity (O4)—affect the outcomes. This analysis provides valuable insights into the stability and reliability of the proposed solutions, helping to identify which factors most significantly influence the optimization process.

When the Distance Weighting parameter for Accessibility (O1) is varied, the analysis shows a moderate sensitivity measure. This indicates that changes in this parameter lead to a noticeable shift in the preference for solutions that are closer to amenities, suggesting that the optimization is somewhat sensitive to how distance is prioritized. As a result, urban planners should carefully consider how they weight accessibility distances, as this can impact which solutions are deemed optimal.

For Safety (O2), varying the Accident Rate Weight reveals a high sensitivity measure, leading to significant changes in safety prioritization. This finding implies that the safety outcomes are highly responsive to how accident rates are factored into the objective. Even small adjustments in the accident rate weighting can cause major shifts in the prioritization of safety in the final solutions. Therefore, planners need to be particularly cautious when determining how to incorporate accident data into their safety assessments.

On the other hand, the Environmental Quality (O3) objective shows a low sensitivity measure when the Pollution Index parameter is varied. This suggests that changes in pollution levels have minimal impact on the allocation of green spaces, indicating a stable objective that is less influenced by minor variations in pollution data. Consequently, environmental quality appears to be consistently prioritized, regardless of small changes in pollution, making it a reliable objective in the optimization process.

Finally, the Social Inclusivity (O4) objective exhibits moderate sensitivity when the Inclusivity Score is varied. This results in adjustments to infrastructure aimed at supporting vulnerable groups, indicating that social inclusivity is somewhat responsive to changes in how inclusivity is scored. This responsiveness suggests that planners should carefully consider how they measure and prioritize inclusivity to ensure that infrastructure improvements align with the needs of all demographic groups.

Overall, the sensitivity analysis highlights the importance of understanding which parameters most strongly influence the optimization outcomes. The high sensitivity of safety to accident rate weighting, for example, underscores the need for careful consideration in safety planning, while the low sensitivity of environmental quality suggests a more stable and reliable objective. By identifying the most influential factors, urban planners can ensure that their selected solutions are robust and effective across a range of scenarios.

The Fig. 5 display how variations in parameters affect each of the four objectives: Accessibility (O1), Safety (O2), Environmental Quality (O3), and Social Inclusivity (O4). Each graph shows the objective value across low, medium, and high parameter variations, illustrating the sensitivity of each objective to changes in these parameters. This analysis helps in understanding which objectives are most impacted by parameter changes, guiding more informed decision-making in urban planning.

Comparative analysis

The performance of the NSGA-III algorithm was compared against other multi-objective optimization algorithms, namely Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-Objective Teaching-Learning Based Optimization (MOTLBO) (Patil et al. 2024; Sethi, Prajapati,

Table 4 Sensitivity analysis of objective functions

Objective Function	Parameter Varied	Sensitivity Measure	Impact on Solution
Accessibility (O1)	Distance Weighting	Moderate	Shift in preference for closer amenities.
Safety (O2)	Accident Rate Weight	High	Significant change in safety prioritization.
Environmental Quality (O3)	Pollution Index	Low	Minimal impact on green space allocation.
Social Inclusivity (O4)	Inclusivity Score	Moderate	Changes in infrastructure for vulnerable groups.

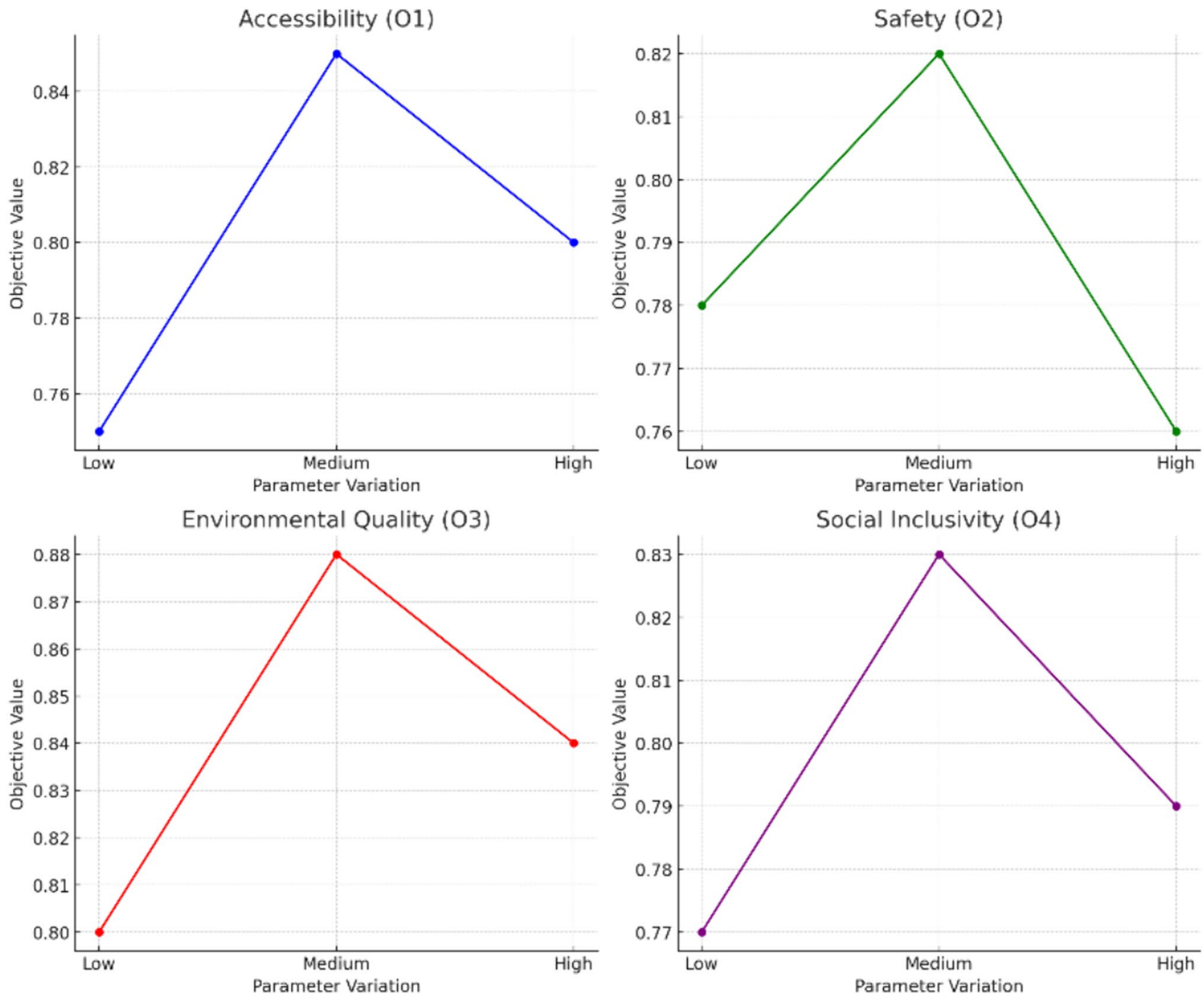

Fig. 5 Sensitivity analysis graphs for each objective

et al. 2024). The comparison focused on critical performance metrics, including Spread, Generalization Distance, and Hypervolume, which are essential for evaluating the diversity, robustness, and quality of the solutions generated by each algorithm. Table 5 presents a summary of these performance metrics, highlighting why NSGA-III is considered superior.

NSGA-III achieves a moderate spread ranging from 0.05 to 0.07, indicating that its solutions are well-distributed across the Pareto front. This spread is optimal for urban planners as it offers a diverse set of solutions, providing a range of trade-offs between objectives like Accessibility (O1), Safety (O2), Environmental Quality (O3), and Social Inclusivity (O4). In contrast, MOPSO exhibits a higher spread of 0.08 to 0.10, which, while suggesting diversity, may result in solutions that are more dispersed and less closely aligned with the optimal Pareto front, potentially compromising optimality. On the other hand, MOTLBO shows a lower spread between 0.04 and 0.06, indicating a more concentrated set of solutions that likely converges

Table 5 Comparative performance metrics of optimized solutions

Metric	NSGA-III	MOPSO	MOTLBO
Spread	Moderate (0.05–0.07)	High (0.08–0.10)	Low (0.04–0.06)
Generalization Distance	Low (0.08–0.10)	Moderate (0.10–0.12)	Low (0.07–0.09)
Hypervolume	High (0.85–0.88)	Moderate (0.80–0.83)	High (0.86–0.89)

better but with less diversity, potentially limiting flexibility in decision-making.

Regarding generalization distance, NSGA-III maintains a low range of 0.08 to 0.10, indicating that its solutions are robust and well-generalized across various scenarios. This robustness makes NSGA-III's solutions more applicable to different urban planning contexts. MOPSO, however, shows a moderate generalization distance between 0.10 and 0.12, suggesting that its solutions might not generalize as effectively, with a potential tendency towards overfitting to specific optimization conditions. MOTLBO, similar to NSGA-III, achieves a low generalization distance of 0.07 to 0.09, indicating robust solutions. However, when combined with its lower spread, this suggests that while MOTLBO's solutions are robust, they may not offer the wide applicability seen with NSGA-III.

In terms of hypervolume, NSGA-III scores highly, ranging from 0.85 to 0.88, indicating that it covers a large portion of the objective space and that its solutions are close to the true Pareto front. This high hypervolume means that NSGA-III provides urban planners with a comprehensive set of optimal trade-offs. MOPSO, with a moderate hypervolume between 0.80 and 0.83, covers a reasonable portion of the objective space but doesn't reach the same level of optimality as NSGA-III, possibly leading to less efficient trade-offs. MOTLBO also achieves a high hypervolume of 0.86 to 0.89, slightly higher than NSGA-III, suggesting effective coverage of the objective space. However, this higher hypervolume, combined with its lower spread, indicates that MOTLBO's solutions, while optimal, may be less diverse, offering fewer alternatives.

The data in Table 5 clearly shows that NSGA-III strikes the best balance between diversity, robustness, and optimality. Its moderate spread ensures a well-distributed set of solutions, its low generalization distance guarantees that these solutions are robust and applicable across different scenarios, and its high hypervolume indicates that the solutions are close to the true Pareto front. Compared to MOPSO and MOTLBO, NSGA-III provides a superior set of solutions that are both diverse and optimal, making it the best choice for multi-objective optimization in urban planning scenarios where multiple competing objectives must be balanced effectively.

Figure 6 illustrates the distribution of optimized solutions (S1, S2, S3) across four key objectives: Accessibility (O1), Safety (O2), Environmental Quality (O3), and Social Inclusivity (O4). The radar chart visually represents how each solution performs relative to these objectives, providing a clear view of the trade-offs involved. Solution S1 is characterized by relatively high scores in accessibility (0.85) and environmental quality (0.82), but it shows moderate performance in safety (0.78) and social inclusivity (0.75). Solution S2 provides a more balanced performance

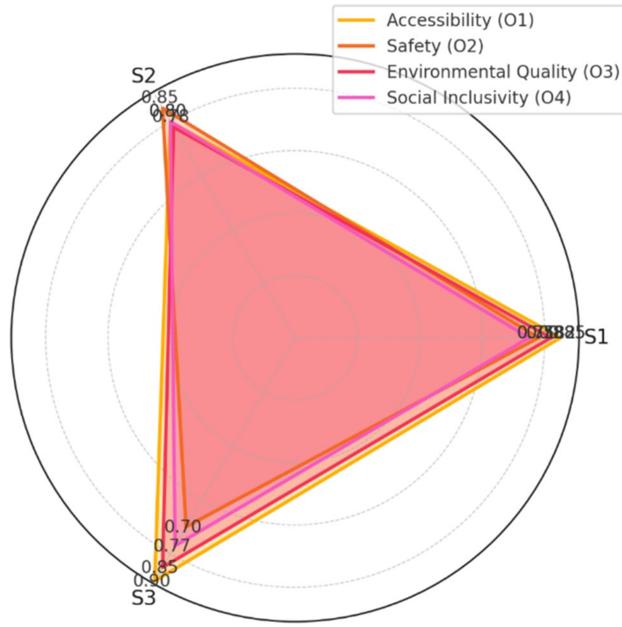

Fig. 6 Distribution of solutions across objectives

across the objectives, with strong safety (0.85) and social inclusivity (0.80) scores, though it slightly lags in accessibility (0.80) and environmental quality (0.78). Solution S3 maximizes accessibility (0.90) and environmental quality (0.85), but this comes at the cost of lower safety (0.70) and social inclusivity (0.77). This chart helps urban planners and decision-makers understand the trade-offs between the different objectives and select solutions that best align with their priorities, whether that be a balance across objectives or a focus on maximizing specific ones.

Trade-Offs and policy implications

Figure 7 presents a comparative analysis of different urban planning scenarios, focusing on the performance of four key objectives: Accessibility (O1), Safety (O2), Environmental Quality (O3), and Social Inclusivity (O4). The bar chart provides a clear comparison of how each scenario impacts these objectives. Scenario 1 shows strong performance in accessibility (0.88) and environmental quality (0.80), but it compromises on safety (0.75) and social inclusivity (0.77). Scenario 2 prioritizes safety (0.89) and social inclusivity (0.83), resulting in slightly lower scores in accessibility (0.82) and environmental quality (0.77). Scenario 3 focuses on maximizing environmental quality (0.90) and accessibility (0.85), but this comes at the cost of lower safety (0.78) and social inclusivity (0.75).

This comparison highlights the trade-offs that urban planners must consider when selecting a planning approach. For instance, prioritizing environmental quality might require

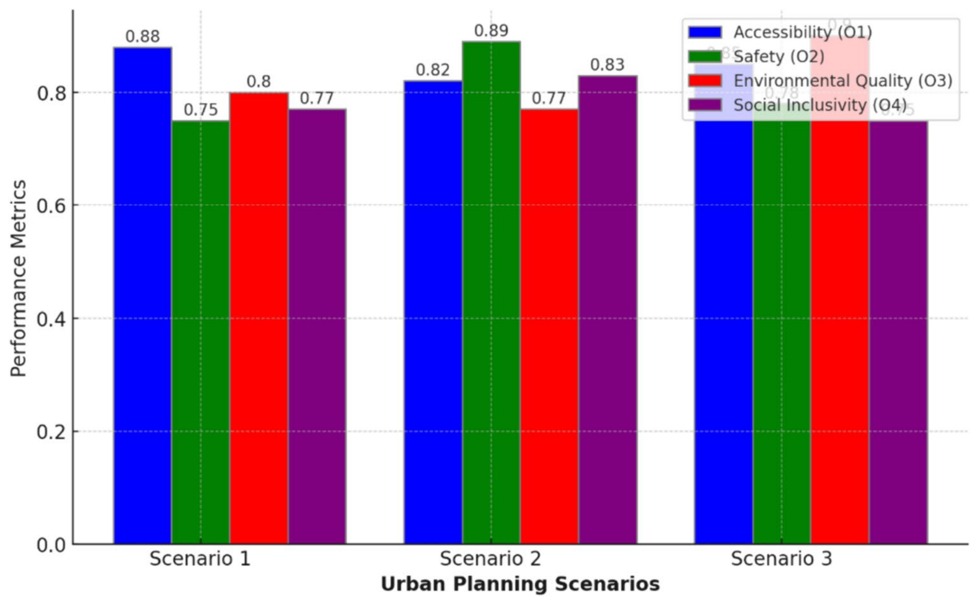

Fig. 7 Comparative analysis of different urban planning scenarios

sacrificing some safety or inclusivity, while a focus on safety could limit accessibility and environmental improvements. The chart helps decision-makers understand the implications of their choices and select scenarios that best align with their strategic goals for urban development.

Discussion and policy implications

The results of the optimization process using the NSGA-III algorithm offer valuable insights into the trade-offs between accessibility, safety, environmental quality, and social inclusivity in urban planning. This section interprets these results, provides policy recommendations, and outlines the limitations of the study along with directions for future research.

The results indicate that achieving a perfect balance among all four objectives—accessibility, safety, environmental quality, and social inclusivity—is challenging due to the inherent trade-offs. For instance, solutions that maximize accessibility and environmental quality, such as Solution S3, tend to compromise safety and social inclusivity. Conversely, solutions like S2 that prioritize safety and social inclusivity might result in slightly lower accessibility and environmental quality. This balance is crucial for urban planners who must weigh these trade-offs against the specific needs and priorities of their communities. The radar and bar charts provided in Figs. 6 and 7 visually demonstrate these trade-offs, helping planners to better understand the implications of their decisions.

Based on the optimization results, the following policy recommendations (see Table 6) are suggested to enhance urban walkability while balancing the key objectives.

These policy interventions are designed to address the specific trade-offs highlighted by the optimization results. For example, enhancing public transportation and mixed-use developments can improve accessibility without significantly compromising environmental quality or safety. Similarly, expanding urban green spaces can boost environmental quality while improving social inclusivity by making urban areas more welcoming to all residents.

Conclusion

This study has explored the application of the Non-dominated Sorting Genetic Algorithm III (NSGA-III) to the complex challenge of optimizing urban walkability, a critical component of sustainable city planning. By addressing multiple, often conflicting objectives—accessibility,

Table 6 Suggested policy interventions for enhancing walkability

Objective	Policy intervention
Accessibility (O1)	Implement mixed-use developments and enhance public transportation infrastructure.
Safety (O2)	Improve pedestrian infrastructure, including crosswalks, lighting, and traffic calming measures.
Environmental Quality (O3)	Expand urban green spaces and enforce pollution control regulations.
Social Inclusivity (O4)	Ensure all urban developments include accessible infrastructure for vulnerable groups.

safety, environmental quality, and social inclusivity—the study offers a novel approach to creating walkable urban environments that enhance the quality of life for residents.

The results demonstrate that NSGA-III is a powerful tool for balancing the diverse objectives inherent in urban planning. The algorithm's ability to generate a diverse set of Pareto-optimal solutions provides urban planners with a range of viable options, each representing different trade-offs between key factors. This flexibility is crucial in real-world urban planning, where no single solution can satisfy all objectives simultaneously.

The sensitivity analysis further validated the robustness of the proposed solutions, highlighting the importance of carefully considering the weightings and parameters used in the optimization process. The comparative analysis with other optimization algorithms underscored the superiority of NSGA-III in generating well-distributed and high-quality solutions, making it particularly well-suited for the complex, multi-dimensional nature of urban walkability optimization.

The findings of this study offer actionable insights for urban planners and policymakers, suggesting targeted interventions that can enhance walkability while balancing competing objectives. These recommendations can guide the development of more livable, inclusive, and sustainable urban environments.

However, the study also acknowledges certain limitations, such as the need for further refinement of the objective functions and the potential for extending the research to larger and more complex urban settings. Future research could explore the integration of economic considerations, the application of NSGA-III in different cultural and geographical contexts, and the development of even more comprehensive models that incorporate additional dimensions of urban sustainability.

In conclusion, this research contributes significantly to the field of urban planning by providing a comprehensive and practical framework for optimizing urban walkability using advanced multi-objective optimization techniques. By fostering more walkable cities, this approach supports broader goals of public health, environmental sustainability, and social equity, ultimately promoting the development of more sustainable and resilient urban spaces.

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Data availability The datasets generated and analyzed during the current study are not publicly available due to restrictions related to privacy and confidentiality but are available from the corresponding author on reasonable request.

Declarations

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

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