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A data-driven multi-objective approach to improving the quality of the urban space: The character of Sydney's public domain

Mohammed Makki [a,*], Jordan Mathers [b], Linda Matthews [a], James Melsom [a], Nimish Biloria [a], Blake Raymond [a], Jacky Cheung [a], Kim Ricafort [a]

[a] University of Technology Sydney, Sydney, Australia
[b] SJB, Sydney, Australia

A R T I C L E I N F O

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A B S T R A C T

This article investigates the quality of urban spaces, emphasizing the need for systematic quantification to guide design and policy decisions towards sustainable urban development. It highlights significance of the high-quality urban environments and the opportunities for translating quality as a measurable metric in the design stage. The study builds on previous research that identifies the key variables and percentages to calculate the four qualitative traits of beauty, ambience, safety, and comfort; identified through the analysis of urban suburbs in Sydney, Australia. The current phase of the research advances this work by using the calculated qualitative metrics as design objectives in the development of urban spaces through a generative multi-objective evolutionary algorithm (MOEA). This approach aims to integrate quantitative assessments into urban design, offering insights into creating inclusive and high-quality urban areas. Moreover, the research also proposes a method for integrating AI as a visualisation tool to convey the design output to the end user. The research underscores the complexity of urban quality, incorporating physical, social, and psychological dimensions, and advocates for a numerically driven approach to urban planning and design practices.

1. Introduction

The quality of urban spaces and their relationship with the surrounding urban tissues has been an ongoing focus for architects, urban designers, planners, as well as policymakers (Garau & Pavan, 2018). However, the criteria for defining a good quality urban space have evolved over the past century (Amin, 2002). Quantifying the quality of urban space enables a more systematic approach to urban development, providing an evidence-based framework for policy and design decisions. Furthermore, understanding what makes a high-quality urbanscape can support future sustainable urban design, promote environmentally friendly practices and help to reduce the impacts of climate change on urban communities (Dempsey et al., 2011). Ultimately, improving urban quality can increase economic growth, reduce social inequalities and improve public health (Rydin et al., 2012).

The sustainability and longevity of the urban environment, as well as the satisfaction, comfort, and sense of belonging of its inhabitants, determine the quality of urban space (Carmona, 2010). These features of urban design encompass both physical and abstract aspects, such as auditory, visual, and tactile elements (Amin, 2002). Wayfinding, image identity, community, public life, physical fabric, and their intricacies are all included in a “good” urban environment, and visual identity is dispersed across paths, nodes, edges, districts, and landmarks (Amin, 2002). The psychological perception of space and the experiences of its inhabitants also play a role in the development of urban quality (Amin, 2002). Individuals and communities have varying opinions on urban space, rendering it necessary to examine experiences from multiple perspectives in order to learn how to enhance quality (Lynch, 1960).

Establishing the quality of urban space and determining how to improve it requires measurement and analysis of the fundamental values shaping urban environments. The study described in this paper was the second phase of the authors' research on the quantification of urban quality. Phase 1 of the research consisted of an examination of existing methods of quantifying quality, followed by development of a new

* Corresponding author at: School of Architecture, Faculty of Design Architecture and Building, University of Technology Sydney, 702-730 Harris Street, Ultimo, NSW 2007, PO Box 123, Australia.
E-mail address: mohammed.makki@uts.edu.au (M. Makki).
URL: http://www.uts.edu.au (M. Makki).

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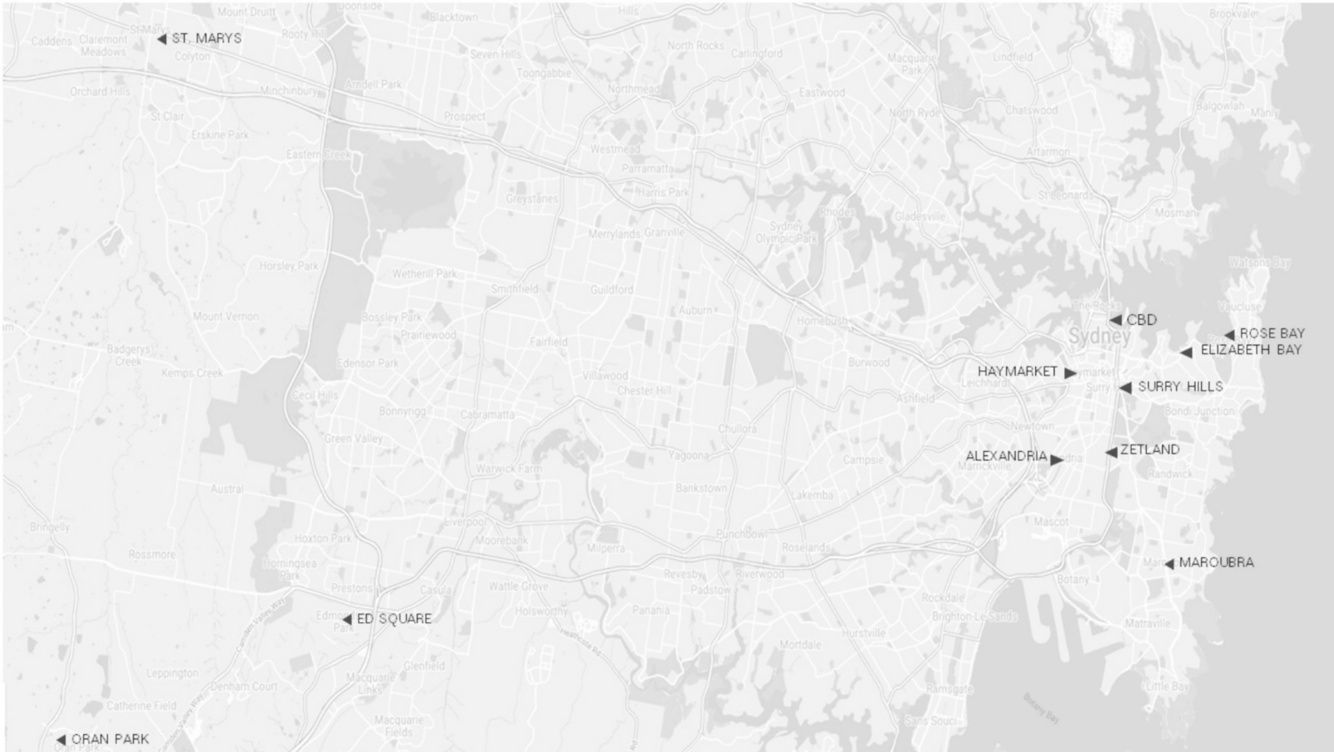

Fig. 1. Sydney locations selected for image procurement. Locations were chosen based on variation of urban conditions.

method comprised of an image survey, image segmentation, video analysis and GIS correlation analysis, and its application to selected locations in Sydney, Australia. Key qualitative traits were identified and categorised based on correlations between the results of these analytic approaches.

In this first phase of the research, the main metrics connected to each qualitative trait were numerically quantified, thus serving as guidelines for initiatives that seek to improve urban quality. One such initiative, which is the focus of this research, is the integration of the collected data within a generative design model that facilitates the analysis of existing urban quality and the generation of new proposals.

This paper presents an extensive summary of the findings of the first phase of the research and establishes the current state of the art, in which the numerical representations of four subjective qualitative perceptions of urban space are presented. This is followed by the integration of these metrics within a generative design process that presents a highly adaptable model that can be modified by designers based on their own analyses of urban space. Finally, the research ends with an AI approach to visualisation, also embedded as part of the proposed design model.

2. Background and context

Measuring urban quality is an extensive and complex field of research; despite a multitude of initiatives that aim to determine the meaning of urban quality (and how to measure it), there lacks a consensus on a single definition. It is observed that different methods of analysis of urban quality have resulted in different interpretations and conclusions (Wesz et al., 2023). However, despite this, it remains critical for designers to quantify urban quality to provide an objective framework to judge urban environments. Doing so provides a better understanding of how various design strategies impact the quality of urban space before its implementation. This evidence-based approach helps designers make informed decisions, as well as facilitates communication among stakeholders. This is applicable in both the analysis of existing urban space, but more importantly, in the design of new urban spaces. Through the quantitative representation of urban quality, deeper insights can be attained into the strengths and weaknesses of urban areas, particularly from the perspective of the resident.

Recent technological advancements have made it possible to measure urban elements more efficiently and accurately. This has led to a range of methods to understand and improve urban quality, each utilising different approaches to data collection and analysis with varying degrees of success. Physical site observation, employed by researchers Cheung (2018) and Liu (2018), involves collecting specific data such as traffic flow, pedestrian density and activity patterns through direct observation. This provides contextual understanding and immediate access to phenomena such as space usage at different times of the day. However, it is time consuming as it requires extensive periods to be spent on site to collect data across different times and seasons for a comprehensive analysis. In an attempt to circumvent the limitations of physical observation, the integration of GIS (Geographical Information System) with SVI (Google Street View Images) assisted computer vision (CV) and machine learning (ML) presents a more digitally driven and efficient approach. Toohey et al. (2022) utilised this combination to analyse infrastructure quality and availability for bicycle-friendly urban forms. Digital methods enable the collection of larger sample sizes compared to physical observation, enhancing time efficiency. However, SVI can introduce biases by providing views primarily from vehicles rather than pedestrians, and large sample sizes require careful consideration of demographic variations. Despite this, visual analytics is a powerful tool for understanding pedestrian response to urban space. Andrienko and Andrienko (2013) used trajectories and bird's eye views to analyse movement data, with interactive techniques and computational processing. This allows for a large amount of data to be collected; however assumptions are required to translate people's interactions with urban space to the qualitative definition of the space.

In contrast to these large-scale digital methods, small scale volunteer experiments offer a different approach that captures more intimate responses to the urban space. A smaller sample size allows for methods to be used that would otherwise not be possible through large scale

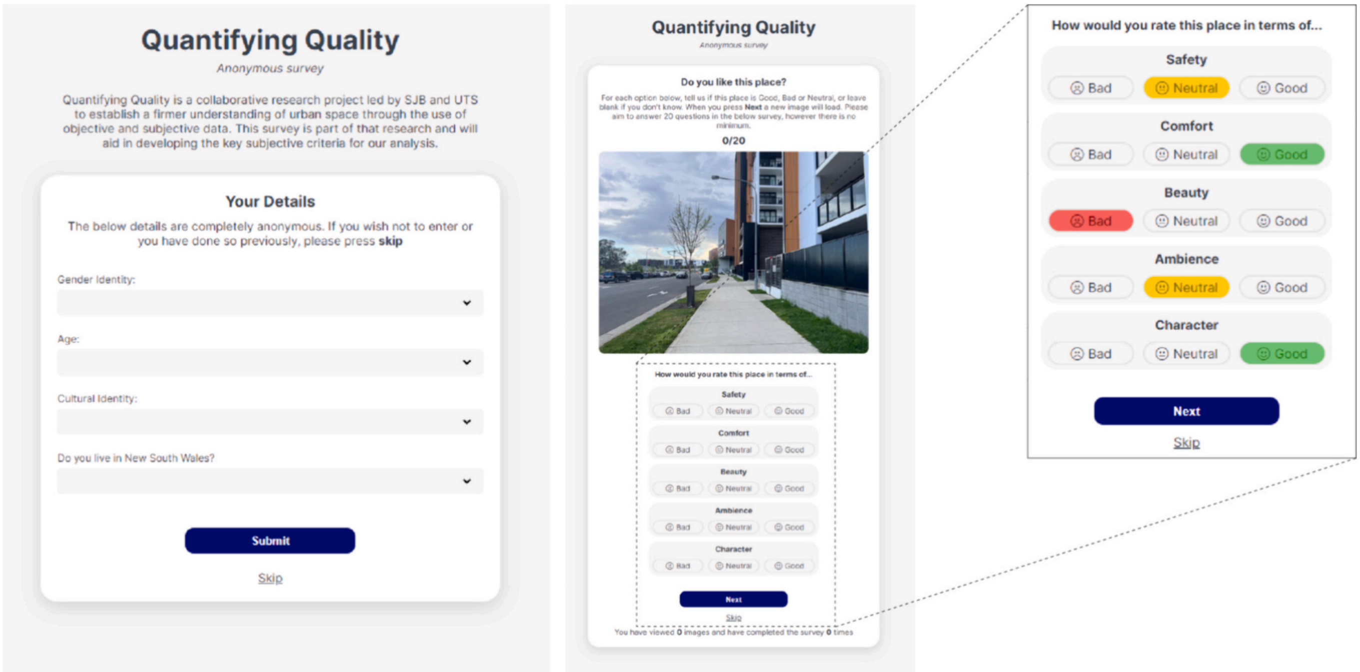

Fig. 2. The survey format shared to participants. The survey was published through an online platform and shared through public social media channels.

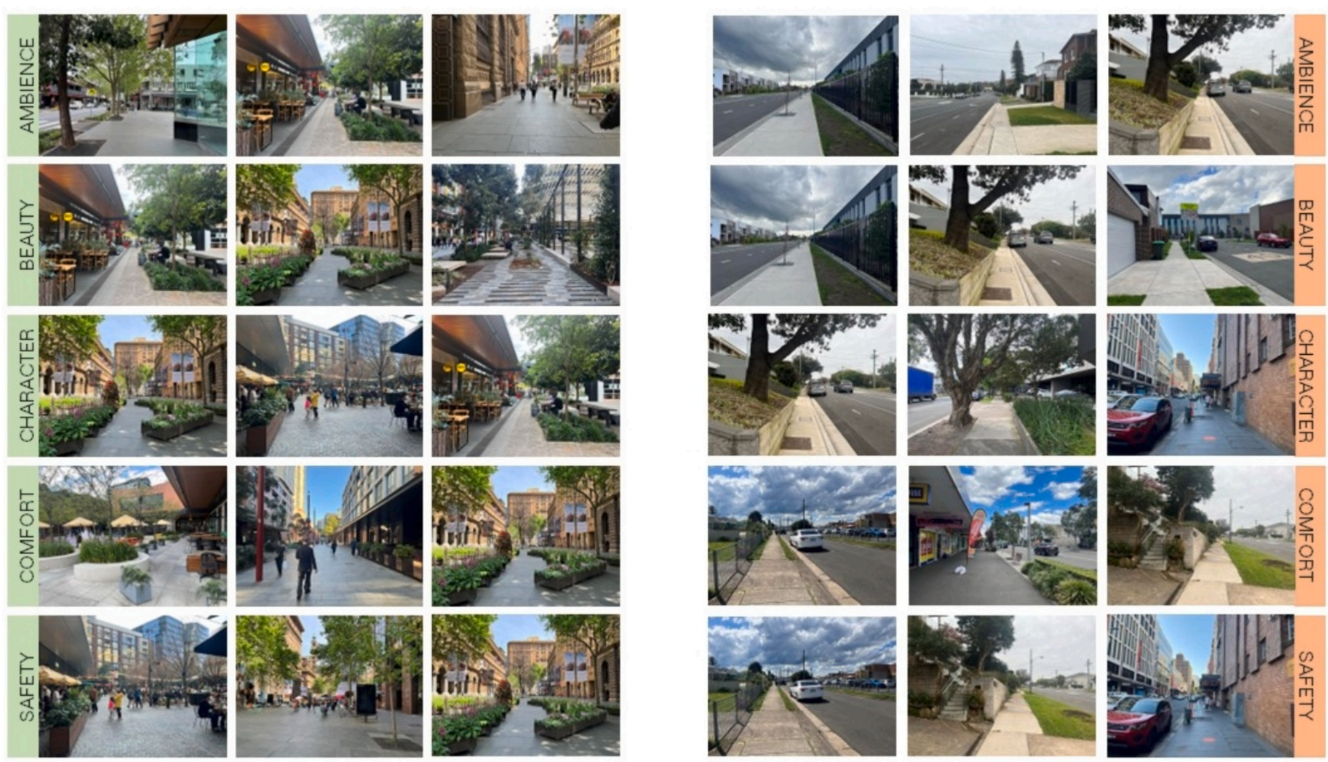

Fig. 3. Survey results were ranked for each urban trait from best to worst, with best and worst three from each trait presented here.

analyses. One such example is research by Hollander and Foster (2016) in which portable EEG monitors were used to record participants' physiological and psychological responses as they walked through residential streets, allowing for the collection and translation of human experience to quantitative data sets. As expected, the small sample size (driven primarily by time constraints) is a major limitation to this approach. However, the data collected provides insights not accessible to the more conventional large scale analysis methods.

Regardless of the various advantages and limitations to the different methods of qualitative analysis of urban space, each approach uniquely contributes to a deeper understanding of urban environments. Although it may be impossible to provide a single method that combines all these approaches into one, it is important to acknowledge that there is not a single optimal approach to qualitative analysis of urban space. Yet, it is

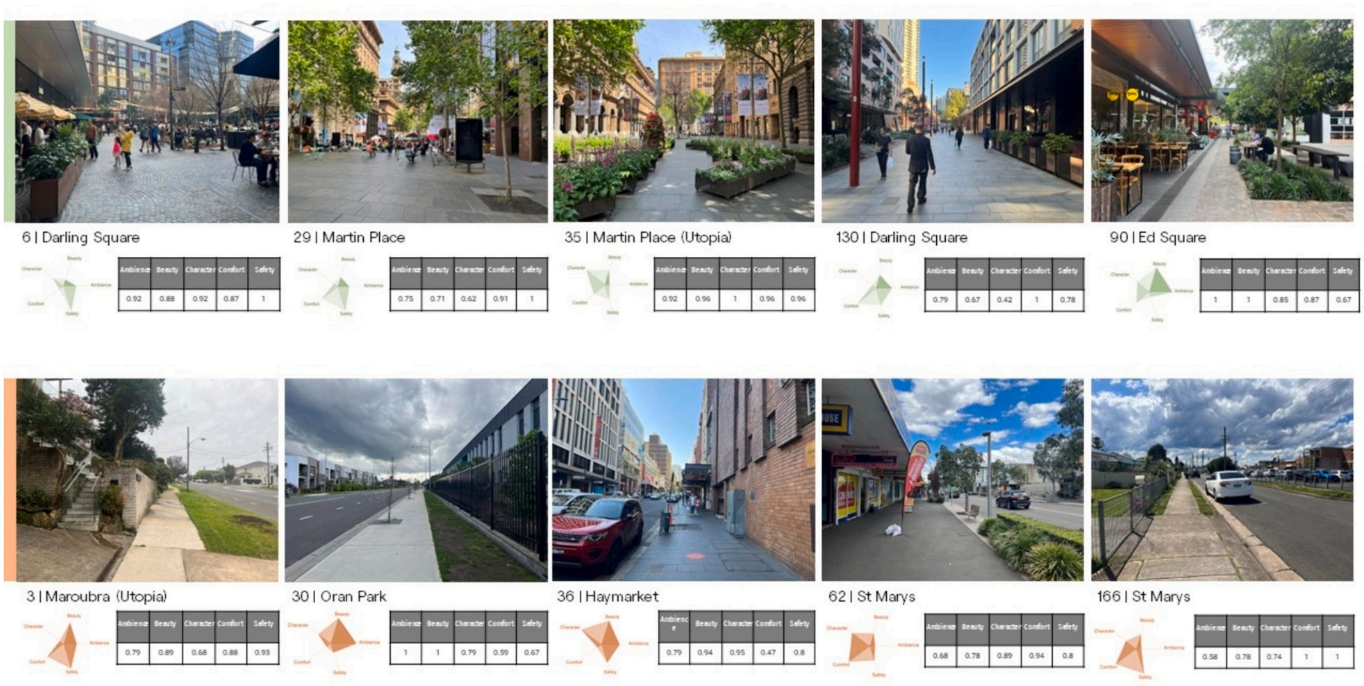

Fig. 4. The survey results for each trait were then normalised and combined to present the best and worst images overall across all traits.

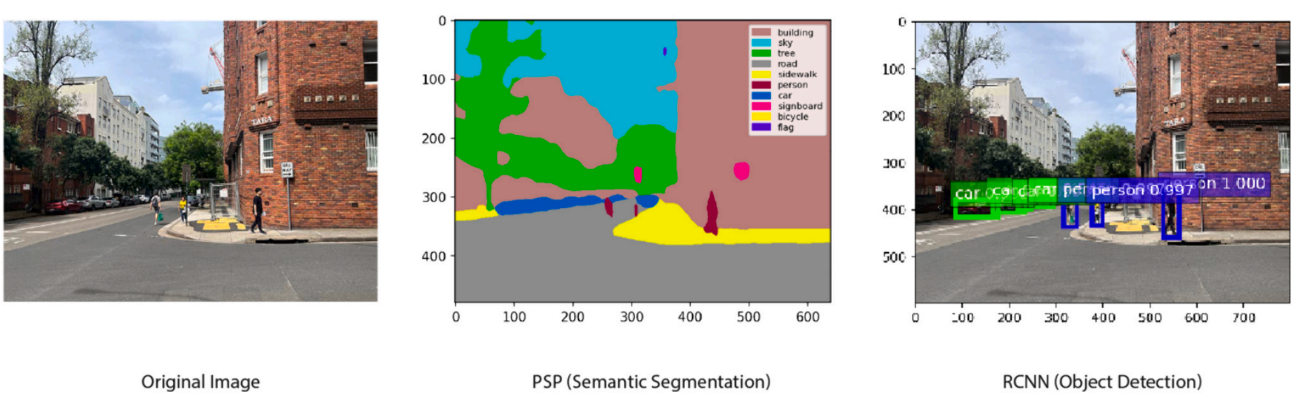

Fig. 5. An example of the image segmentation algorithms used. An original image (left) is used as an input for the two image segmentation algorithms. The first, PSPNet (middle) calculates the occurrence of an urban trait through a percentage, while the second, R-CNN (right) calculates the occurrence of an urban trait through the number of times it appears in the image.

clear that most attempts to analyse urban quality are either objective or subjective (Garau & Pavan, 2018). In this context, the method for data collection to quantify the quality of urban space developed for this research relies on both objective and subjective modes of collection and analysis. Although a more robust explanation of the method can be found in the first phase of this research, an extensive summary of the developed method is presented below. The data collected from this method is used as the input parameters for the generative design model presented in following sections.

2.1. Quantifying urban quality

As stated, the objective of the developed analysis method is to identify a set of quantifiable metrics to measure the quality of the built environment. To do so, the primary focus of the study was the city of Sydney and its surrounding suburbs. 13 urban locations across Sydney were selected for analysis, representing a diverse range of urban typologies, such as high-rise urban fabrics of the central business district (CBD), to the low-rise suburban housing that dominates Sydney's west (Fig. 1). Photographs were taken from each location to mimic a pedestrian's experience in the urban environment (as opposed to the vehicle-based Google Street View images used in similar studies). The photos were then embedded within an online survey that asked participants to rank the urban quality presented in the photo as good, neutral or bad, across five key traits: safety, comfort, beauty, ambience and character (Fig. 2). The identification of these five key traits was primarily based on how a pedestrian of the urban space can relate to their urban environment, using key words that are void of complex design language. Similar approaches have been implemented in studies that responded to pedestrian interactions with urban space (Talavera-Garcia & Soria-Lara, 2015). Additionally, utilising photographs that captured the pedestrian view was critical to ensure the respondents assessment of the images were reflective of their perception as a pedestrian (not the vehicle).

The survey collected responses from 236 individuals (approximately 50 % of the respondents were from Sydney, with the other 50 % living internationally), with a total of 4791 individual image responses. The images were ranked and sorted based on their scores against each trait individually (Fig. 3), as well as ranked and sorted based on their

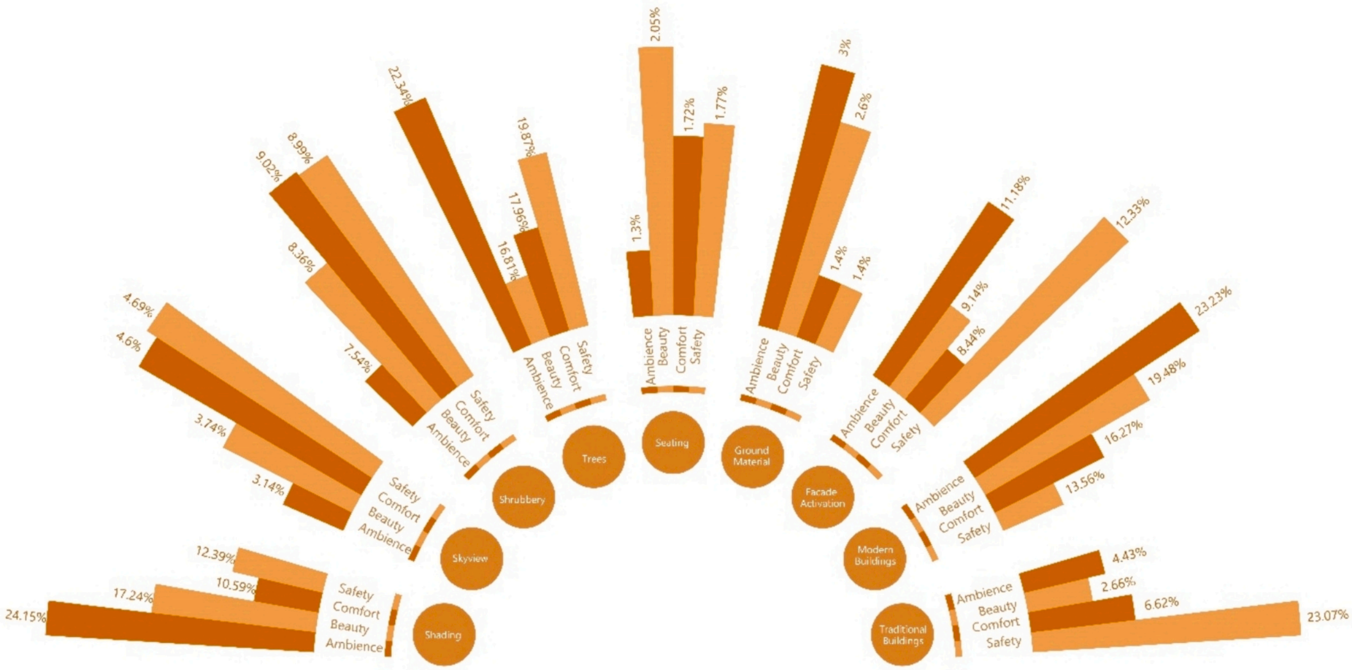

Fig. 6. The quantification of the four key traits of safety, comfort, ambience and beauty, against the urban conditions extracted from the survey results.

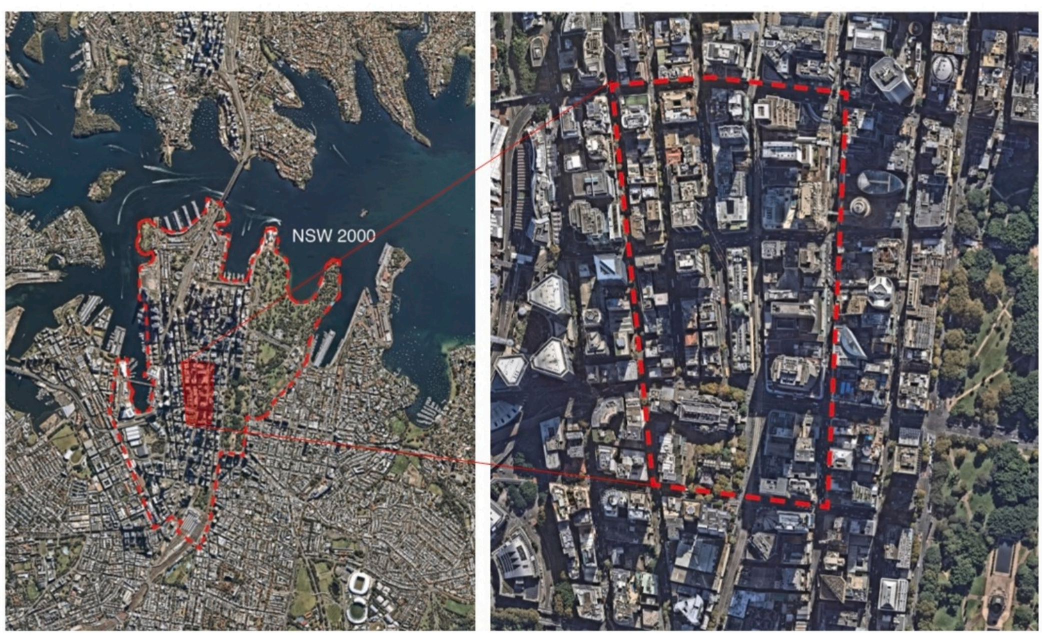

Fig. 7. The site selected was the Town Hall Area in Sydney's CBD. Above is the site's location relative to the greater Sydney CBD.

collective performance on all 5 traits (Fig. 4).

The ranked images were then analysed using image segmentation, primarily through the use of pyramid scene parsing (PSPNet – semantic segmentation) in which the algorithm identifies the percentage of an image that falls within a specific category (such as sky, trees, ground, buildings) and a region-based convolutional neural network (R-CNN – object detection), which identifies the numerical occurrence of those categories (Fig. 5).

The overlay of the algorithms' results produced a clear and comprehensive understanding of the urban characteristics that contribute to the survey respondents' high or low ranks. This analysis identified nine quantitative metrics that contributed substantially to each urban trait with respect to the images evaluated:

- shading
- skyview
- low-level greenery (shrubbery)
- trees
- seating
- ground material variation
- surrounding facade activation (i.e. buildings accessible to the public)
- modern buildings/facades

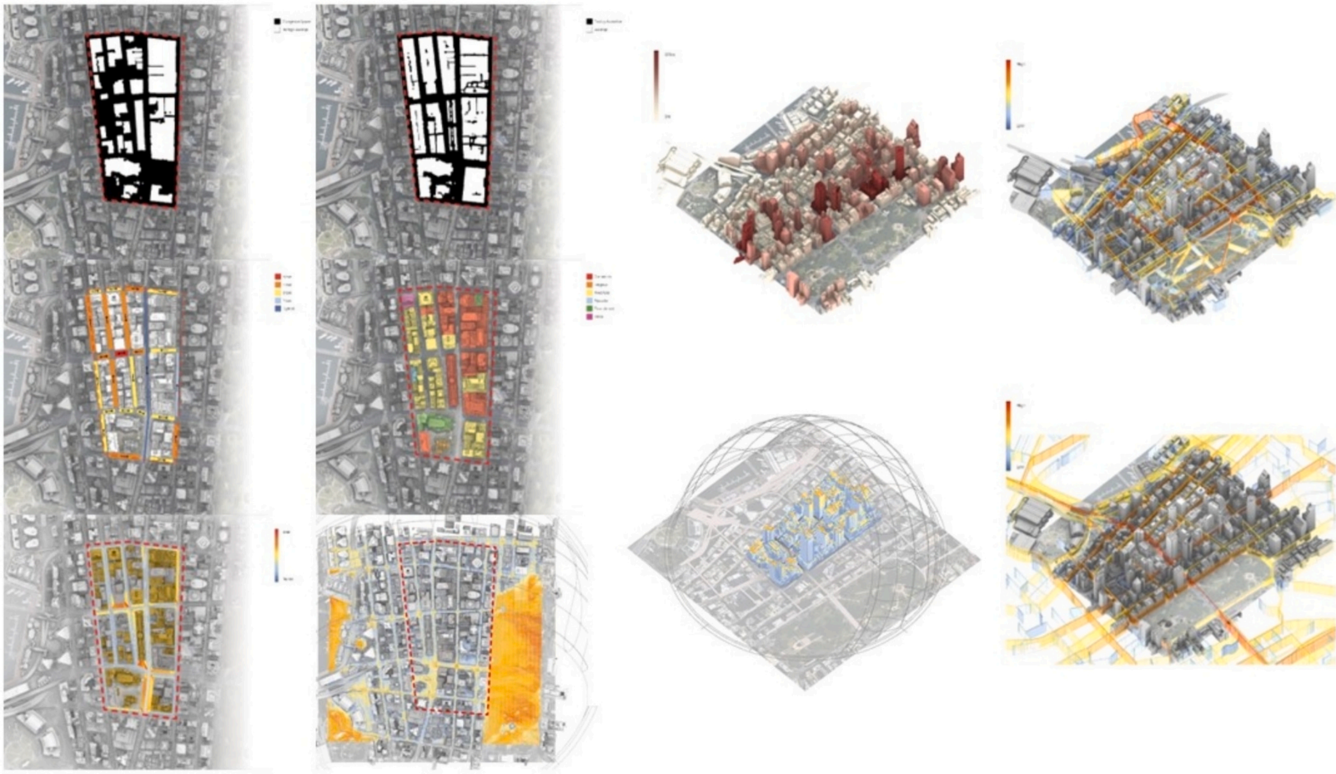

Fig. 8. The selected site was analysed against a multitude of metrics, including solar gain, space syntax, street widths, building heights, pedestrian sidewalk widths, and building functions.

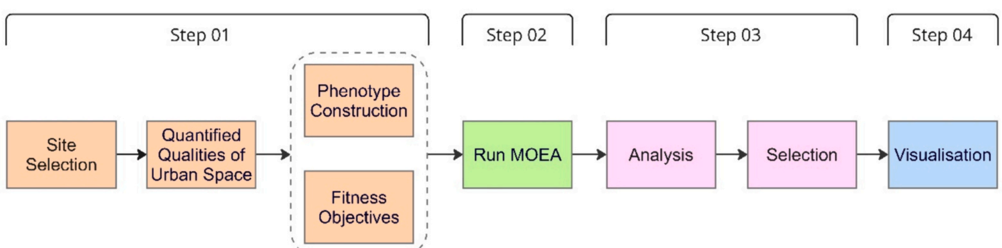

Fig. 9. A simplified diagram of the experiment's pseudo code. The four steps are formulating the design problem, running the algorithm, analysis of the results, and visualisation.

- traditional building/facades

In doing so, the survey results and image analysis made it possible to specifically represent each qualitative trait with a percentile distribution of each urban metric (Fig. 6). (Note that no clear pattern was discerned for character, probably due to survey respondents defining it differently, so that trait was omitted from the remainder of the research).

Through the precise quantification of each trait, it is now possible to use this information as a design parameter in the conceptual development of an urban proposal, specifically through its integration in a generative model. This is presented in the following sections, in which a design experiment is conducted on an urban site in Sydney to demonstrate the opportunities of integrating the quantified metrics presented above in the design process.

2.2. Case study

The site selected for the quantification of urban quality was the Town Hall area in Sydney's CBD, a commercial, tourism and financial hub that forms the core of the city's central district (Fig. 7). Despite its vibrant and dynamic ambience and intertwined modern high-rises and heritage buildings, Town Hall area has few green spaces and plazas for the size of its residential and transient population, leading to a sense of urban congestion.

The selected site covers the superblock bounded by Kent Street, Pitt Street, King Street, and Bathurst Street, with the Queen Victoria Building (QVB) in the centre. Most of the buildings are commercial, with some mixed use (commercial and office, with minor residential). A figure-ground analysis (FGA) revealed few publicly accessible spaces, other than shopping centre interiors and the Town Hall Arcade (a small plaza). Another FGA highlighted the area's high proportion of heritage buildings, which cannot be modified or demolished. A third FGA revealed an abundance of arcades, alleyways and an underground network that are currently underutilised for public access, with some alleyways very inactive in comparison to the rest of the site. Analysis indicated multiple wide and some extremely narrow sidewalks, and that most roads are one-way with 3–4 lanes, with a light-rail-only road (other than for car access to local buildings) cutting through the site along George Street. The commercial and touristic nature of the site means these roads experience constant high traffic and frequent congestion.

Fig. 10. The step-by-step process for the formulation of the design problem. Each variable in the steps above is a parameter used by the MOEA to create variation and evolve a new solution for evaluation, for the objective of optimisation.

Table 1
The four design objectives used in the MOEA. Each objective was calculated through the quantified traits presented in Section 2.1.

Fitness Objective	Image ID	Location	Normalised Values	Quality Metrics											
				Skyview	Shrubs	Trees	Seating	Shading	Facade Activation	Glass (facade)	Traditional Material (facade)	Modern Material (facade)	Material Variations (pavement)	Traditional Facade Normalised	Modern Facade Normalised
Ambiance	90	Ed Square	1	3	11	25	1.63	32.49	21.72	5.46	0	31.61	4	0.00	100.00
	160	Darling Square	0.95	0.95	7.6	29.45	3.705	27.512	1.254	1.368	0	20.007	6	0.00	100.00
	35	Martin Place	0.91	5.46	14.56	17.29	0	13.6864	0.4823	1.729	14.9513	0	1	100.00	0.00
	19	Surry Hills	0.91	0.91	1.82	32.76	0.7735	35.6993	12.6763	17.6722	7.2163	26.9269	3	21.14	78.86
	6	Darling Square	0.9	5.4	2.7	7.2	0.378	11.34	19.791	12.186	0	37.602	1	0.00	100.00
	Average Percentage			3.14	7.54	22.34	1.30	24.15	11.18	7.68	4.43	23.23	3.00	16.03	83.97
Beauty	90	Ed Square	1	3	11	25	1.63	32.49	21.72	5.46	0	31.61	4	0.00	100.00
	35	Martin Place	0.81	4.86	12.96	15.39	0	12.1824	0.4293	1.539	13.3083	0	1	100.00	0.00
	160	Darling Square	0.84	0.84	6.72	26.04	3.276	24.3264	1.1088	1.2096	0	17.6904	6	0.00	100.00
	6	Darling Square	0.76	4.56	2.28	6.08	0.3192	9.576	16.7124	10.2904	0	31.7528	1	0.00	100.00
	118	Ed Square	0.68	5.44	8.84	11.56	5.0252	7.6024	7.0584	2.448	0	16.3404	1	0.00	100.00
	Average Percentage			3.74	8.36	16.81	2.05	17.24	9.41	4.19	2.66	19.48	2.60	12.02	87.98
Comfort	118	Ed Square	1	8	13	17	7.39	11.18	10.38	3.6	0	24.03	1	0.00	100.00
	35	Martin Place	0.91	5.46	14.56	17.29	0	13.6864	0.4823	1.729	14.9513	0	1	100.00	0.00
	173	Surry Hills	0.88	0.88	13.2	16.72	0	14.3176	27.3944	14.6872	4.2856	25.0888	2	14.59	85.41
	130	Darling Square	0.87	6.09	4.35	6.09	0.2175	5.9334	3.654	6.9774	1.5399	32.2422	1	4.56	95.44
	29	Martin Place	0.86	2.58	0	32.68	0.9804	7.8432	0.3096	1.3158	12.3066	0	2	100.00	0.00
	Average Percentage			4.60	9.02	17.96	1.72	10.59	8.44	5.66	6.62	16.27	1.40	28.91	71.09
Safety	29	Martin Place	1	3	0	38	1.14	9.12	0.36	1.53	14.31	0	2	100.00	0.00
	118	Ed Square	0.99	7.92	12.87	16.83	7.3161	11.0682	10.2762	0.3564	2.8512	0.3564	1	88.89	11.11
	6	Darling Square	0.98	5.88	2.94	8.82	0.4116	12.348	21.5502	13.2692	0	40.9444	1	0.00	100.00
	35	Martin Place	0.95	5.7	15.2	18.05	0	14.288	0.5035	1.805	93.651	0	1	100.00	0.00
	173	Surry Hills	0.93	0.93	13.95	17.67	0	15.1311	28.9509	15.5217	4.5291	26.5143	2	14.59	85.41
	Average Percentage			4.69	8.99	19.87	1.77	12.39	12.33	6.50	23.07	13.56	1.40	62.97	37.03

Table 2
The MOEA settings and simulation runtime for the experiment.

Simulation size		Algorithm settings	
Generation size	50	Mutation rate	1/n (n = no. of variables)
Generation count	100	Crossover probability	0.9
Population size	5000	Mutation distribution index	20
Number of variables	1984	Crossover distribution index	20
Size of search space	3.5×10^{218}	Simulation runtime	9 h: 58mins: 5 s

A solar analysis on the ground plane revealed spots that receive the most solar gain, namely the Town Hall Arcade, road intersections and the four road segments surrounding the QVB. Solar analysis of the building facades revealed that most low-level building facades and south-facing facades receive minimal sunlight. To analyse the overall connectivity of the area, betweenness centrality was calculated at both the vehicular and pedestrian scale, identifying spaces with high connectivity to every other space and thus high spatial quality (Stonor, 2011). Vehicular analysis found high connectivity along Druitt and Park Streets and off branching roads such as Elizabeth and Pitt Street, coinciding with the observed high vehicular traffic. The results of pedestrian analysis coincided with observations of pedestrian traffic through the site, with George Street identified as a popular route. Most buildings are less than ~100 m tall; taller buildings, double or triple the average building height, are dispersed around the site (Fig. 8).

3. Method

The primary objective of the conducted qualitative analysis of the urban space (presented above) was the translation of subjective perceptions to quantifiable numerical representations extracted from the geometric assessment of the urban context. In doing so, a correlation (or 'link') is established between what the urban space looks like, and how it performs against the 4 qualitative traits (safety, beauty, ambience, comfort). The main advantage of this is that it can now be used as input data in an optimisation algorithm that works to create design solutions that exhibit high correlations between the urban space, and people's perception of its quality. In this context, the four qualitative traits are used as design objectives for the optimisation process; however, due to their being multiple design objectives that may potentially be in conflict with one another (for example, safety is correlated with a high number of traditional buildings, while beauty is correlated with a low number), an optimisation algorithm is needed that can address this conflict.

As such, a multi-objective evolutionary algorithm (MOEA) is employed due to its ability to respond to a complex design problem (comprised from multiple conflicting design objectives) through a population-based model that generates an array of diverse solutions (De Jong, 2006). Through the use of a MOEA, there is no need to combine the design objectives into a single objective, thereby generating a diverse set of solutions that independently respond to each design goal (Deb, 2001). Such an approach allows for the 'discovery' of design solutions that may have not been considered through a conventional design approach (Coello et al., 2021).

In design, the value of MOEAs is amplified; the performance-based metric approach to a design problem allows designers to integrate climatic, environmental, and design metrics as key drivers for the algorithm, drivers that are usually in conflict with one another, thus negating the need to apply trade-off decisions in the early stages of the design process. The past decade has witnessed the development of a number of design tools (embedded within mainstream 3d modelling software) that offer access to MOEAs without requiring the user to develop text-based coding skills (Abdulmawla et al., 2017; Harding & Brandt-Olsen, 2018; Makki et al., 2018; Vierlinger, 2013), resulting in a considerable rise in the application of MOEAs in design (Koenig et al., 2020; Makki et al., 2022; Raymond et al., 2024; Showkatbakhsh et al., 2021; van Ameijde et al., 2022). As such, and in the context of the significant advantages of employing an MOEA for a numerically driven design problem comprised from multiple conflicting design objectives, the presented research employs the NSGA-2 algorithm (a MOEA developed by Deb et al., 2002), which is embedded within the design tool Wallacei (Makki et al., 2018).

The design objectives used in the MOEA are the four qualitative

Fig. 11. A sample solution set from Generation 0. This first generation is a randomly contains solutions that are randomly generated by the algorithm in an attempt to cast the widest nest across the search space.

traits, which in turn are defined by the 9 urban metrics (presented in Fig. 6). The presented experiment comprises a four-step process: The formulation of the design problem (including site selection, construction of the design solution, identification of design parameters for the algorithm to control, and the calculation of the fitness objectives for the algorithm to optimise towards); the running of the MOEA; Analysis and selection of the optimal design solution, and ai-assisted visualisation of the selected solution (Fig. 9). The following sections present each step of this process.

3.1. Experiment setup

3.1.1. Formulating the design problem

The desired qualities of an urban space vary based on factors such as context, culture and climate. The method used in this research to design a quantifiably successful urban space enables multiple parameters to be altered and adapted to fit the preferences and scenario of each unique site. The adaptability of this methodology allows for the formulation of a design problem specific to a chosen site, in this case, Sydney's Town Hall.

The site covers a 350 m × 625 m area centred on the Queen Victoria Building, with many features offering potential for urban intervention. They include multiple lanes and alleyways currently used for service access, non-heritage buildings, and multiple one-way roads.

Conventional approaches to public space integrate high density locales through singular contained typologies. In contrast, the proposed model employs a distributive approach, recognising existing areas of open ground such as roads, lanes and alleyways as opportunities for new public urban spaces. These areas could be expanded and improved by the removal of buildings that fit certain criteria (in this case, lacking heritage protection and lower than a predefined height limit of 70 m), as explored in the current experimental redesign of Town Hall.

3.1.2. Constructing the phenotype

The design goal was to revitalise Town Hall, achieving a higher-quality spatial experience through improved distribution of greened public spaces, repurposing lanes, alleys, roads and non-heritage buildings, using the results from the data collected via the urban analysis in the distributed survey. The first step in the construction of the phenotype was to identify heritage buildings, buildings of cultural significance, and buildings above a certain height (set here at 70 m) as "fixed" and unlikely to be demolished in the near future. This list of retained buildings can be modified to suit the unique context of each site, allowing a designer to select or omit elements to retain or remove (Fig. 10a).

To refine the list of removable buildings, the aforementioned lanes and alleys were identified, and buildings nonadjacent to them were culled. This guaranteed that only buildings occupying space connected to pedestrianised lanes or alleys could be removed (Fig. 10b). The MOEA was then given control of which buildings to remove and convert into

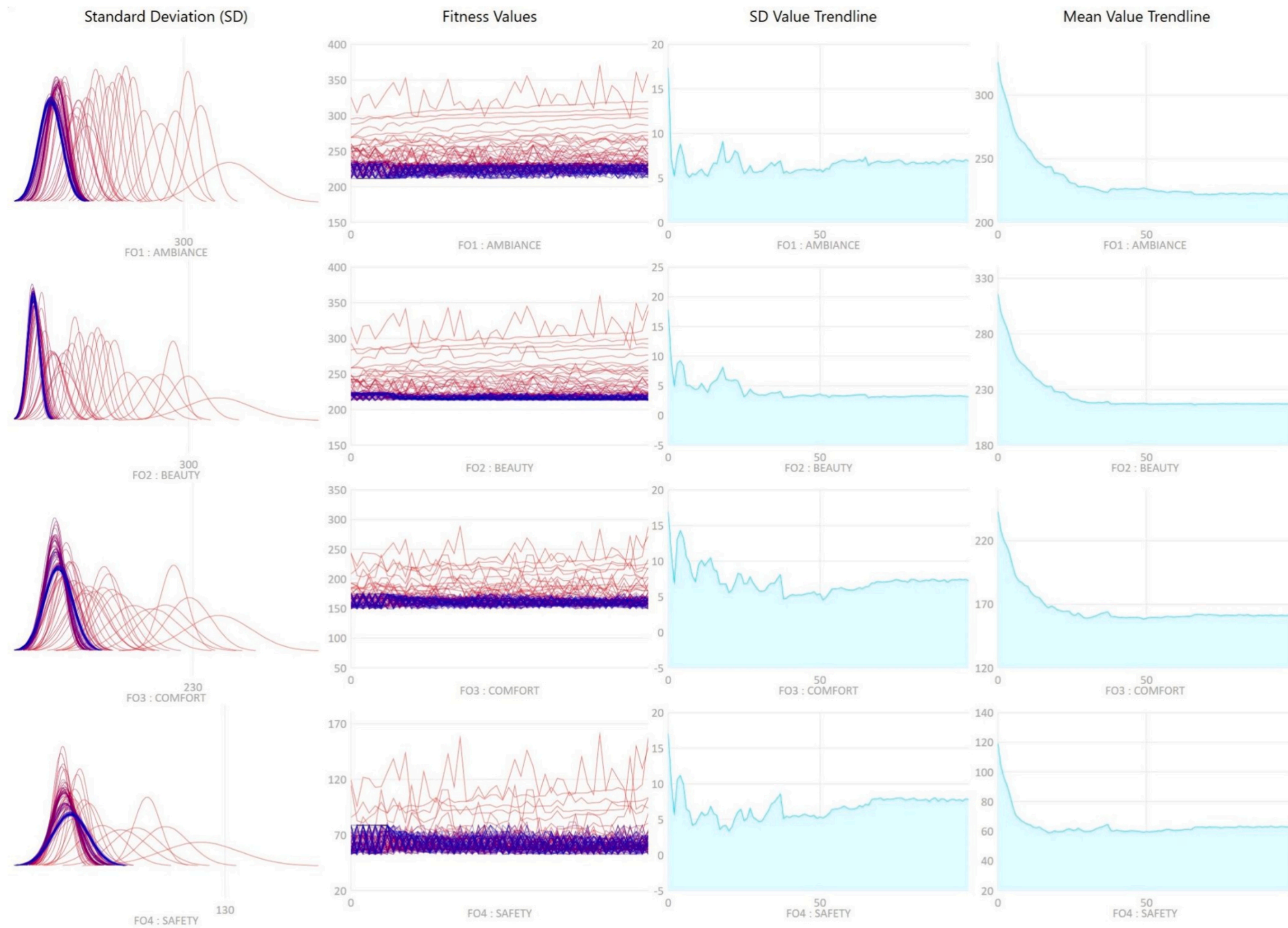

Fig. 12. The results (data) of the MOEA. Each row in the figure represents the fitness values for all solutions in the population for a given fitness objective. The fitness values are presented through four modes, all for the purpose of identifying two key characteristics: Variation of solutions in the population and convergence of solutions towards a global (or local) optima.

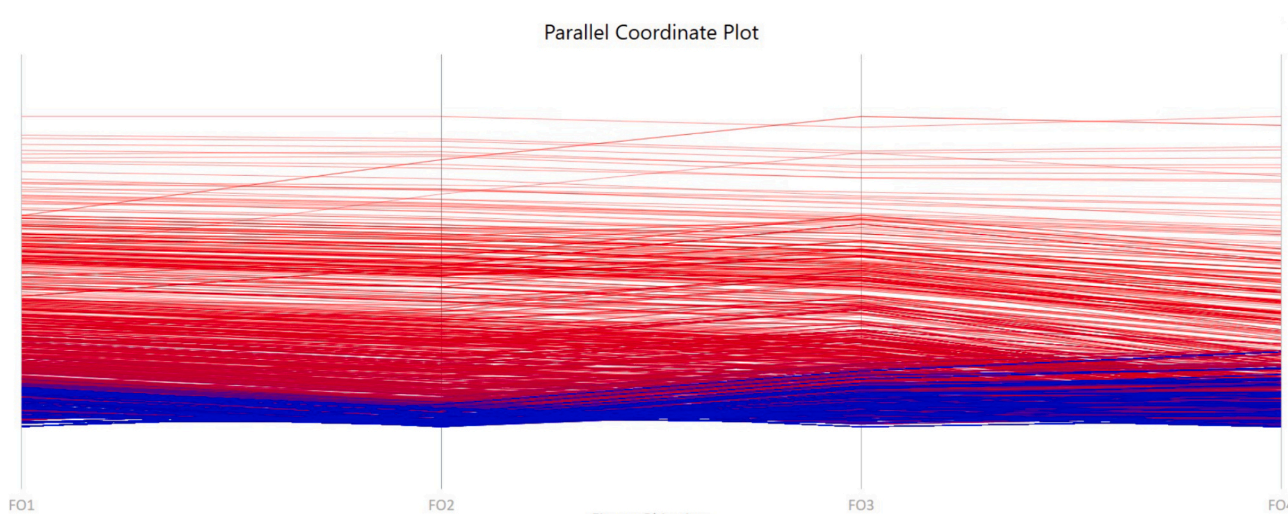

Fig. 13. The fitness values of all solutions in the population (across all objectives) presented through a parallel coordinate plot. Each Y-axis represents a fitness objective, and each solution in the population represented through a single line. The gradient red to blue presents solutions from start to end of the simulation (respectively). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 14. The top 25 solutions extracted from the simulation for further evaluation and selection.

VISIBILITY	SKYVIEW	PERCENTAGE OF ISOVIST VISIBILITY FROM PLAZAS	PERCENTAGE OF ISOVIST VISIBILITY FROM STREETS	ACCESSIBILITY	DIFFERENCE BETWEEN EXISTING AND NEW SYNTAX (CONNECTIVITY)	AVERAGE SYNTAX (CONNECTIVITY)
PERCENTAGE OF LOW SYNTAX (CONNECTIVITY)	PERCENTAGE OF HIGH SYNTAX (CONNECTIVITY)	ENVIRONMENTAL	AREA OF GREEN SPACE	PROXIMITY BETWEEN NEW OPEN SPACES AND EXISTING POINTS OF INTEREST	PROXIMITY BETWEEN NEW OPEN SPACES TO EACH OTHER	
PROXIMITY OF POINTS OF INTEREST TO UNDERGROUND NETWORK ENTRANCES	PERCENTAGE OF TREES TO QUALITY TARGET	PERCENTAGE OF LOW LEVEL GREENERY COMPARED TO QUALITY TARGET	NUMBER OF TREES	NUMBER OF LOW LEVEL GREENERY		
SOLAR	PERCENTAGE OF HIGH SOLAR GAIN ON PLAZAS	PERCENTAGE OF HIGH SOLAR GAIN ON STREETS	TOTAL PERCENTAGE OF HIGH SOLAR GAIN	SHADING	URBAN	FACADE ACTIVATIONN
SEATING	TRADITIONAL FACADE MATERIAL	MODERN FACADE MATERIAL	PAVEMENT MATERIAL VARIATION	HEIGHT OF ADDED VOLUMES COMPARED TO MAX BUILDING HEIGHTS		

Fig. 15. The chosen metrics to analyse (and differentiate) the top 25 design solutions.

public open space and which to retain by modifying variable parameters (termed as 'genes' in the application of evolutionary computation), labelling them 'true' or 'false', for each building (Fig. 10c), with decisions influenced by metrics such as solar gain and skyview. Lanes and alleys were tested for adjacency to newly created open spaces, and if not, removed from the redesign process (Fig. 10d).

To recognise the impacts of reducing building density, the volume of the buildings removed was calculated. This volume was doubled and redistributed evenly among the remaining buildings to demonstrate that the floorspace lost from demolishing certain low-rise buildings can be redistributed in surrounding buildings thus regaining real estate value (Fig. 10e).

These steps established open spaces, lanes and alleyways and supported the next step of selecting roads to convert into pedestrianised spaces. First, all the roads that could be converted were identified. Site analysis of Town Hall showed that roads running east and west experience more vehicular traffic than those running north and south, which are generally narrower and more commonly single-lane, one-way roads. Thus, roads running north and south (excluding George Street due to its tram line) were considered pedestrianisable (Fig. 10f). Then, to cement the establishment of these newly implemented pedestrian spaces, existing points of interest such as the QVB, Sydney Tower, Hyde Park, Sydney Town Hall and locations outside the selected site were identified (Fig. 10g). Existing points of interest are the first layer of analysis in selection of roads to pedestrianise. The proximity of each pedestrianisable road to each point of interest was calculated, and roads with lower average distance scored higher than those with larger distances.

The second layer of analysis is solar gain. This layer interlinks with

Table 3

Each of the 25 solutions were assessed against the metrics identified in Fig. 15. Each metric was given an additional weighting, based on its value to the design goals of the experiment. The solutions were then ranked and the top 5 solutions selected for a second round of assessment.

		TOP SOLUTIONS												
	Weight	0	1	**2**	3	**4**	5	6	7	8	9	10	11	12
PHENOTYPIC INDICATORS		{0;41}	{38;27}	**{39;49}**	{50;22}	**{51;5}**	{59;42}	{63;2}	{63;32}	{66;3}	{67;37}	{68;41}	{68;47}	{71;33}
SKYVIEW	2	0	1.625252	2	1.395158	1.442934	1.52178	1.618256	1.437716	1.32905	1.625252	1.32905	1.885164	1.395528
PERCENTAGE OF ISOVIST VISIBILITY FROM PLAZAS	1	0	0.440867	0.611038	0.637976	0.612352	0.31406	1	0.521682	0.513798	0.440867	0.513798	0.855453	0.599869
PERCENTAGE OF ISOVIST VISIBILITY FROM STREETS	1	1	0.293194	0.068063	0.34555	0.277487	0.293194	0.183246	0.193717	0.34555	0.293194	0.34555	0.277487	0.34555
DIFFERENCE BETWEEN EXISITING AND NEW SYNTAX (CONNECTIVITY)	1	0.840997	0.096184	0.634248	0.507298	0.753399	0.012831	0.584546	0.084188	0.451491	0.096184	0.451491	0.599118	0.539757
AVERAGE SYNTAX (CONNECTIVITY)	1	0.841017	0.096186	0.634239	0.507286	0.753393	0.012807	0.58456	0.084166	0.451477	0.096186	0.451477	0.599108	0.539746
PERCENTAGE OF LOW SYNTAX (CONNECTIVITY)	1	0.970788	0.091224	0.758853	0.680368	0.763719	0	0.671733	0.101048	0.648555	0.091224	0.648555	0.658639	0.676819
PERCENTAGE OF HIGH SYNTAX (CONNECTIVITY)	1	0.888164	0.043277	0.591584	0.425437	0.814445	0.05006	0.40036	0.014593	0.410544	0.043277	0.410544	0.449817	0.514089
AREA OF GREENSPACE	1	0	0.969108	0.918199	0.814903	0.711265	0.967052	0.902337	0.9753	0.809855	0.969108	0.809855	0.898757	0.823599
PROXIMITY BETWEEN NEW OPEN SPACES AND EXISTING POINTS OF INTEREST	1	0.5	0.162715	0.318389	0.03435	0.02487	0.075227	0.141126	0.138519	0	0.162715	0	0.171602	0.034793
PROXIMITY OF NEW OPEN SPACES TO EACHOTHER	1	0	0.407685	0.375934	0.492671	0.498343	0.428489	0.411264	0.410376	0.489026	0.408725	0.489026	0.408556	0.5
PROXIMITY OF POINTS OF INTEREST TO UNDERGROUND NETWORK ENTRANCES	1	0.5	0.162715	0.318389	0.03435	0.02487	0.075227	0.141126	0.138519	0	0.162715	0	0.171602	0.034793
PERCENTAGE OF TREES COMPARED TO QUALITY TARGET	2	0	1.837796	1.93228	0.91901	0.697778	1.746364	1.866148	1.885156	0.866816	1.837796	0.866816	1.808094	1.002826
PERCENTAGE OF LOW LEVEL GREENERY COMPARED TO QUALITY TARGET	2	0.877046	1.008932	0	1.647948	2	1.135056	0.867812	0.870048	1.71894	1.008932	1.71894	0.964964	1.481994
NUMBER OF TREES	1	0	0.929348	0.847826	0.75	0.592391	0.961957	0.940217	0.940217	0.717391	0.929348	0.717391	0.951087	0.875
NUMBER OF LOW LEVEL GREENERY	1	0	0.948864	0.965909	0.931818	0.869318	0.917614	0.840909	0.960227	0.934659	0.948864	0.934659	0.869318	0.980114
PERCENTAGE OF HIGH SOLAR GAIN ON PLAZAS	1	0	0.853296	0.740234	0.407554	0.231334	0.812378	0.825218	0.865365	0.382457	0.853296	0.382457	0.806228	0.441114
PERCENTAGE OF HIGH SOLAR GAIN ON STREETS	1	0	0.860929	1	0.535015	0.544682	0.837317	0.939196	0.870703	0.526931	0.860929	0.526931	0.927991	0.549874
TOTAL PERCENTAGE OF HIGH SOLAR GAIN	1	0	0.881613	0.915173	0.494628	0.423918	0.849825	0.915924	0.892655	0.478938	0.881613	0.478938	0.90102	0.518014
SHADING	2	0	1.737048	1.604784	1.47275	1.591856	1.825582	0.922022	1.479258	1.352988	1.737048	1.352988	1.477208	1.549438
FAÇADE ACTIVATION	2	2	0.073314	0.031036	0.309576	0.265584	0.054796	0.005628	0.076436	0.33127	0.073314	0.33127	0	0.300126
SEATING	2	2	0.405642	0.226032	1.247906	1.42852	0.462734	0.271486	0.397672	1.37751	0.405642	1.37751	0.251308	0.926196
TRADITIONAL FAÇADE MATERIAL	2	0	1.8548	2	1.8548	1.904014	1.804746	2	1.904014	1.804746	1.8548	1.804746	1.952406	1.8548
MODERN FAÇADE MATERIAL	2	0	1.8548	2	1.8548	1.904014	1.804746	2	1.904014	1.804746	1.8548	1.804746	1.952406	1.8548
PAVEMENT MATERIAL VARIATION	2	2	0.49399	1.457928	0.939898	1.457928	1.927878	0.02404	0.49399	1.457928	0.939898	1.927878	0.49399	1.433888
HEIGHT OF ADDED VOLUMES COMPARED TO MAX BUILDING HEIGHT	1	0.520223	0.165516	0	0.919155	0.8971	0.170779	0.503822	0.168498	0.93322	0.165516	0.93322	0.503407	0.850975
TOTAL SCORE:	34	12.93824	18.2943	20.95014	20.16021	21.48551	19.0625	19.56098	17.80808	20.13789	18.74124	20.60784	20.83473	20.6237

		TOP SOLUTIONS											
	Weight	**13**	14	15	**16**	17	18	19	20	21	**22**	23	24
PHENOTYPIC INDICATORS		**{77;25}**	{79;7}	{81;2}	**{82;21}**	{87;21}	{87;30}	{87;44}	{92;12}	{92;42}	**{94;13}**	{99;2}	{99;34}
SKYVIEW	2	1.64543	1.618256	1.68018	1.703434	1.414442	1.540544	1.455866	1.669524	1.486042	1.643382	1.68018	1.395158
PERCENTAGE OF ISOVIST VISIBILITY FROM PLAZAS	1	0.879106	1	0.609724	0.823259	0.377135	0.595269	0.480289	0.757556	0.520368	0.833114	0.609724	0.637976
PERCENTAGE OF ISOVIST VISIBILITY FROM STREETS	1	0.193717	0.183246	0	0.120419	0.193717	0.068063	0.193717	0.356021	0.120419	0.193717	0	0.34555
DIFFERENCE BETWEEN EXISITING AND NEW SYNTAX (CONNECTIVITY)	1	0.574934	0.584546	0.404341	1	0	0.13067	0.11264	0.645481	0.107846	0.582829	0.404341	0.507298
AVERAGE SYNTAX (CONNECTIVITY)	1	0.574924	0.58456	0.404326	1	0	0.130673	0.112619	0.645472	0.107825	0.582819	0.404326	0.507286
PERCENTAGE OF LOW SYNTAX (CONNECTIVITY)	1	0.634714	0.671733	0.479162	1	0.003886	0.090414	0.114474	0.660659	0.110192	0.622154	0.479162	0.680368
PERCENTAGE OF HIGH SYNTAX (CONNECTIVITY)	1	0.438794	0.40036	0.414553	1	0	0.034722	0.064759	0.571834	0.012989	0.475087	0.414553	0.425437
AREA OF GREENSPACE	1	0.891359	0.902337	0.905485	0.769543	0.967052	1	0.980458	0.845357	0.964	0.892943	0.905485	0.814903
PROXIMITY BETWEEN NEW OPEN SPACES AND EXISTING POINTS OF INTEREST	1	0.176972	0.141126	0.187534	0.143055	0.049075	0.188711	0.133396	0.124058	0.16591	0.176801	0.187534	0.03435
PROXIMITY OF NEW OPEN SPACES TO EACHOTHER	1	0.432228	0.411264	0.393272	0.485993	0.431283	0.394618	0.417157	0.492477	0.402799	0.438793	0.393272	0.492671
PROXIMITY OF POINTS OF INTEREST TO UNDERGROUND NETWORK ENTRANCES	1	0.176972	0.141126	0.187534	0.143055	0.049075	0.188711	0.133396	0.124058	0.16591	0.176801	0.187534	0.03435
PERCENTAGE OF TREES COMPARED TO QUALITY TARGET	2	1.57541	1.866148	1.736114	1.12782	1.798292	1.794872	2	1.043696	1.863412	1.713734	1.736114	0.91901
PERCENTAGE OF LOW LEVEL GREENERY COMPARED TO QUALITY TARGET	2	1.27871	0.867812	0.298986	1.104742	1.089018	0.034916	0.6545	1.41999	0.908422	1.15612	0.298986	1.647948
NUMBER OF TREES	1	0.875	0.940217	0.875	0.733696	0.951087	1	0.994565	0.869565	0.956522	0.956522	0.875	0.75
NUMBER OF LOW LEVEL GREENERY	1	0.911932	0.840909	0.9375	0.957386	0.928977	0.965909	0.980114	1	0.90625	0.875	0.9375	0.931818
PERCENTAGE OF HIGH SOLAR GAIN ON PLAZAS	1	0.698462	0.825218	0.660983	0.413849	0.829679	1	0.909847	0.493246	0.866115	0.751261	0.660983	0.407554
PERCENTAGE OF HIGH SOLAR GAIN ON STREETS	1	0.869455	0.939196	0.942971	0.654416	0.846619	0.95308	0.896629	0.552675	0.881268	0.895427	0.942971	0.535015
TOTAL PERCENTAGE OF HIGH SOLAR GAIN	1	0.819503	0.915924	0.846913	0.568287	0.862875	1	0.927354	0.542305	0.899257	0.857838	0.846913	0.494628
SHADING	2	1.400588	0.922022	2	1.536274	1.771498	1.318598	1.574548	1.259634	1.554014	1.679086	2	1.47275
FAÇADE ACTIVATION	2	0.056116	0.005628	0.02009	0.242148	0.057446	0.063334	0.066546	0.299648	0.093052	0.042594	0.02009	0.309576
SEATING	2	0.55232	0.271486	0.28953	0.944746	0.44658	0	0.190904	0.98889	0.374014	0.39652	0.28953	1.247906
TRADITIONAL FAÇADE MATERIAL	2	1.952406	2	2	2	1.8548	1.952406	1.904014	1.8548	1.904014	1.952406	2	1.8548
MODERN FAÇADE MATERIAL	2	1.952406	2	2	2	1.8548	1.952406	1.904014	1.8548	1.904014	1.952406	2	1.8548
PAVEMENT MATERIAL VARIATION	2	1.457928	0.96394	0.46995	0	0.939898	1.457928	0.49399	0.46995	0.49399	0.46995	0.96394	0.46995
HEIGHT OF ADDED VOLUMES COMPARED TO MAX BUILDING HEIGHT	1	0.724689	0.503822	0.070254	0.64358	0.174886	0.031758	0.113239	1	0.201242	0.663787	0.070254	0.919155
TOTAL SCORE:	34	21.74408	20.50088	18.8144	21.1157	17.89212	17.8876	17.80904	20.5417	17.96989	20.98109	19.30839	19.69026

Table 4

The second round of analysis with updated weightings allocated to the urban metrics used in the analysis.

		TOP 5 SOLUTIONS				
	Weight	2	4	13	**16**	22
PHENOTYPIC INDICATORS		{39;49}	{51;5}	{77;25}	**{82;21}**	{94;13}
SKYVIEW	2	2	0	0.466828	**1.217788**	0.654112
PERCENTAGE OF ISOVIST VISIBILITY FROM PLAZAS	1	0	0.004902	1	**0.791667**	0.828431
PERCENTAGE OF ISOVIST VISIBILITY FROM STREETS	1	0	1	0.6	**0.25**	0.6
DIFFERENCE BETWEEN EXISITING AND NEW SYNTAX (CONNECTIVITY)	1	0.139539	0.419851	0	**1**	0.018572
AVERAGE SYNTAX (CONNECTIVITY)	1	0.139539	0.419851	0	**1**	0.018572
PERCENTAGE OF LOW SYNTAX (CONNECTIVITY)	1	0.361785	0.374663	0.03324	**1**	0
PERCENTAGE OF HIGH SYNTAX (CONNECTIVITY)	1	0.272252	0.669363	0	**1**	0.06467
AREA OF GREENSPACE	1	1	0	0.870296	**0.281626**	0.877951
PROXIMITY BETWEEN NEW OPEN SPACES AND EXISTING POINTS OF INTEREST	1	1	0	0.518202	**0.40265**	0.51762
PROXIMITY OF NEW OPEN SPACES TO EACHOTHER	1	0	1	0.682208	**0.870571**	0.740051
PROXIMITY OF POINTS OF INTEREST TO UNDERGROUND NETWORK ENTRANCES	1	1	0	0.518202	**0.40265**	0.51762
PERCENTAGE OF TREES COMPARED TO QUALITY TARGET	2	2	0	1.400694	**0.71571**	1.636804
PERCENTAGE OF LOW LEVEL GREENERY COMPARED TO QUALITY TARGET	2	0	2	1.28083	**1.106726**	1.160216
NUMBER OF TREES	1	0.701493	0	0.776119	**0.38806**	1
NUMBER OF LOW LEVEL GREENERY	1	1	0	0.441176	**0.911765**	0.058824
PERCENTAGE OF HIGH SOLAR GAIN ON PLAZAS	1	0.978792	0	0.898448	**0.35104**	1
PERCENTAGE OF HIGH SOLAR GAIN ON STREETS	1	1	0	0.713287	**0.241006**	0.770329
TOTAL PERCENTAGE OF HIGH SOLAR GAIN	1	1	0	0.805254	**0.293877**	0.883289
SHADING	2	1.442744	0.50279	0	**0.933596**	2
FAÇADE ACTIVATION	2	0	2	0.206284	**1.807228**	0.095056
SEATING	2	0	2	0.57229	**1.169064**	0.313882
TRADITIONAL FAÇADE MATERIAL	2	2	0	1.008336	**2**	1.008336
MODERN FAÇADE MATERIAL	2	2	0	1.008336	**2**	1.008336
PAVEMENT MATERIAL VARIATION	2	2	2	2	**0**	0.730792
HEIGHT OF ADDED VOLUMES COMPARED TO MAX BUILDING HEIGHT	1	0	1	0.807812	**0.7174**	0.739925
TOTAL SCORE:	34	20.036144	13.39142	16.607842	**20.852424**	17.243388

building removal, which can reduce shadowing and permit more sunlight on some open spaces (Fig. 10h).

The third layer of analysis along each road is skyview, which, as the survey data from phase 1 showed, is a metric intrinsic to the overall quality of a space. By favouring roads with a higher amount of view to the sky, there is more opportunity for the algorithm to identify design solutions with the desired amount of optimal skyview (Fig. 10i).

Scores for existing points of interest, solar gain and skyview were

Fig. 16. The selected solution, Gen.82;Ind.21.

added to provide an overall score for each road. The MOEA used these scores to select roads to pedestrianise. The site features nine pedestrianisable roads, the algorithm was given the choice of converting 0–3 roads (Fig. 10j). The highest-ranked and third-highest ranked roads were selected for pedestrianisation; the second highest-ranked road was redesigned to be more pedestrian friendly while maintaining vehicle circulation (Fig. 10k). The second road has a hard-coded design that can be reconfigured to deviate at intervals to reduce traffic speed. Once these changes were implemented, the remaining public domain and the newly pedestrianised public spaces were reintegrated into the design process (Fig. 10l).

The MOEA was used to integrate and designate vegetated spaces, driven primarily by solar gain, which were categorised into four regions (Fig. 10m). Regions that receive most sunlight are designated as spaces for trees, regions that receive sunlight for 45–70 % of the year are designated as spaces for low-level plants and greenery. Regions that receive sunlight for less than 45 % of the year are categorised as having low or no sunlight, then divided by pathways to allow for direct circulation from building entrances to centre lines of pedestrianised roads (Fig. 10n and o).

The results from the survey and image segmentation showed that variation in the material of both ground surfaces and building facades affected the perceived quality of a space. Hence, the MOEA was given control of the materials to apply to ground surface regions and the facades of changeable buildings (Fig. 10p and q). In addition, because the amounts of activated facades and public seating were found to influence overall quality, the MOEA was given control over facade activation. All facades that faced public open space were divided into segments that the algorithm could reduce to reach the desired percentage of activated facades (Fig. 10r). Similarly, seats were distributed throughout the site based on proximity to elements such as trees and greenery, with the MOEA given the ability to cull their number to reach the target.

With all these elements in place, the final step of phenotype construction was the recalculation of skyview (Fig. 10s). The next step of the experiment setup is the definition of the fitness objectives that each phenotype will be tested against (Fig. 10t). These fitness objectives are a numerical representation of the design goals, which the MOEA can optimise towards.

3.1.3. Defining the fitness objectives

The fitness objectives implemented within the evolutionary algorithm were dictated by four of the qualitative traits analysed used in the image survey in the data collection phase of the research: ambience, beauty, comfort and safety. A granular set of quality metrics, identified through the correlations between the image segmentation results and the survey results, defined how these qualitative traits were measured (Table 1).

The percentages (i.e. occurrences of urban conditions) established through the assessment of survey images were converted into percentages within the phenotype using similar methods. The percentage of skyview was calculated by dividing the total number of outward-directed vectors by the number obstructed by an object, building or tree. Percentages of trees and low-level plants were calculated by dividing the total number of analysis points by the number of points

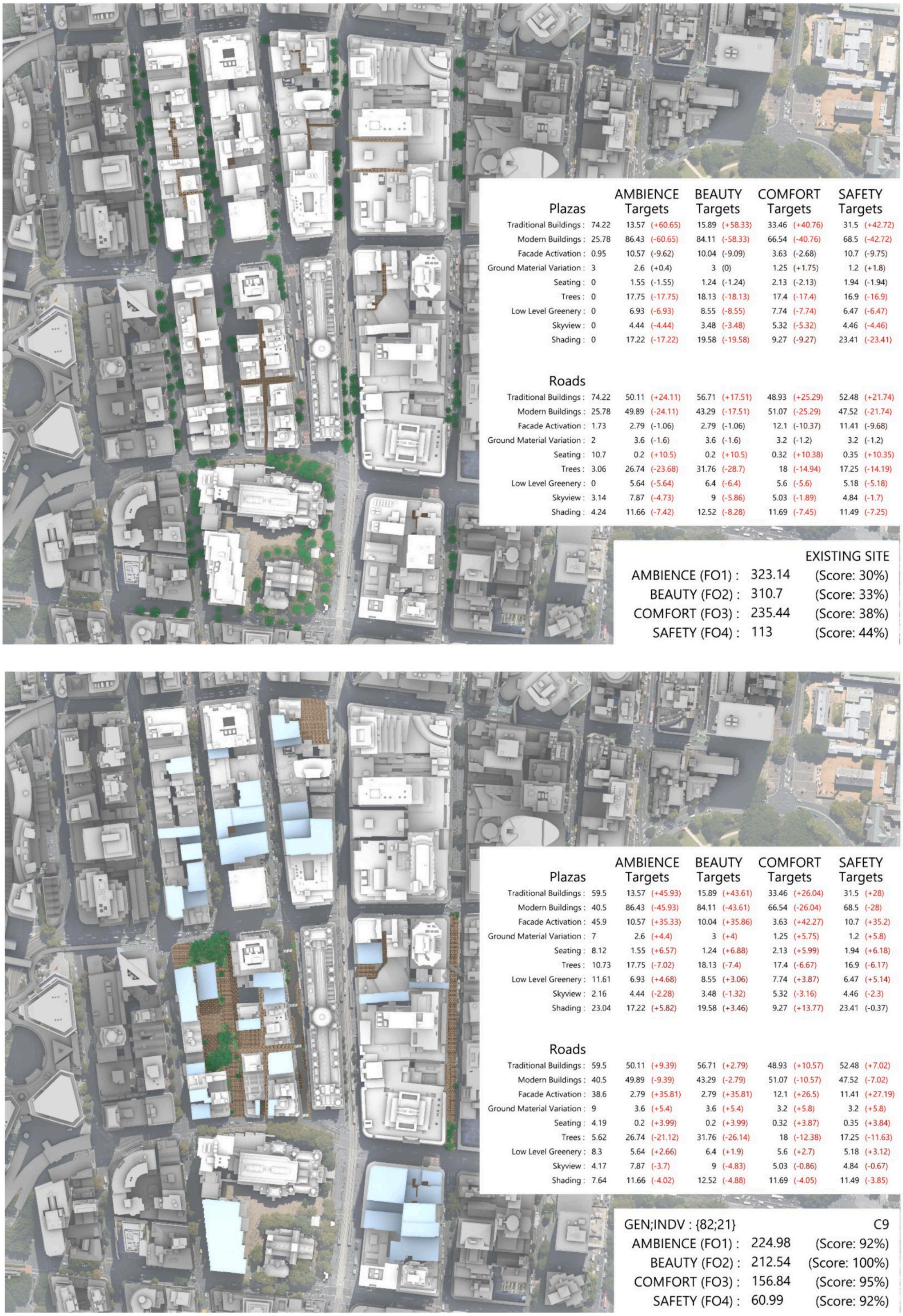

Fig. 17. Comparison of the current urban setting to the urban proposal presented in solution Gen.82;Ind.21.

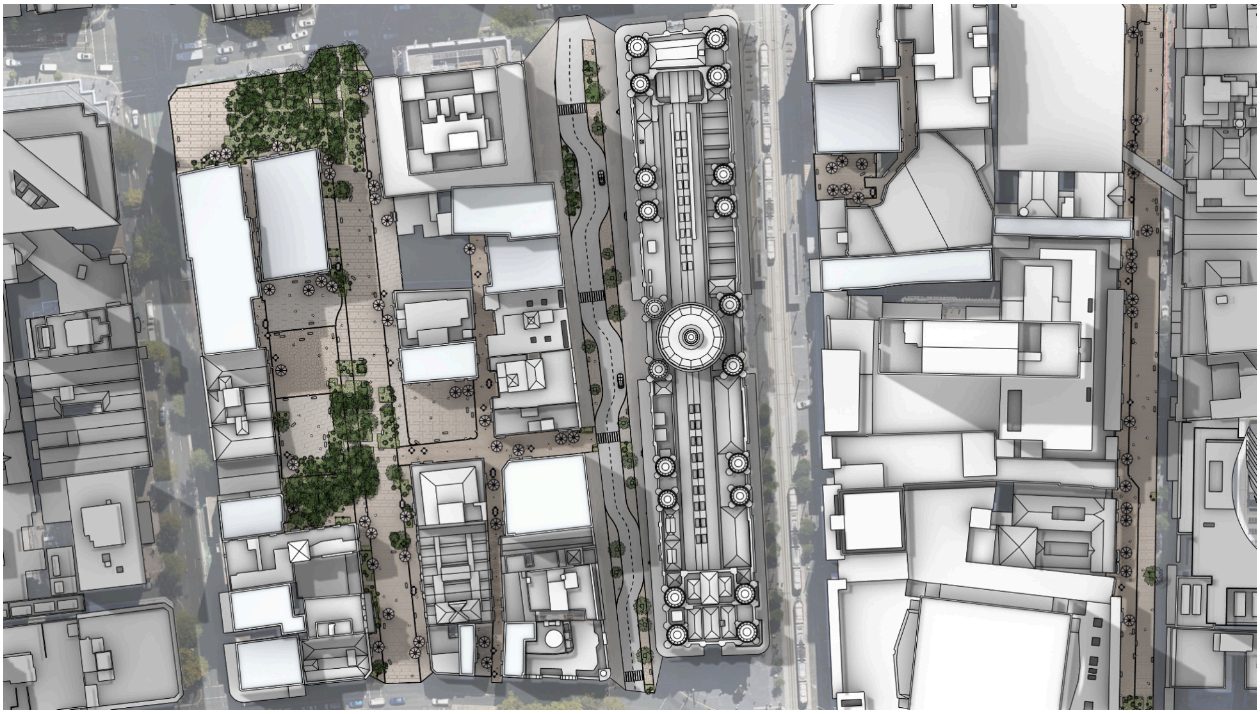

Fig. 18. Top view of the selected solution.

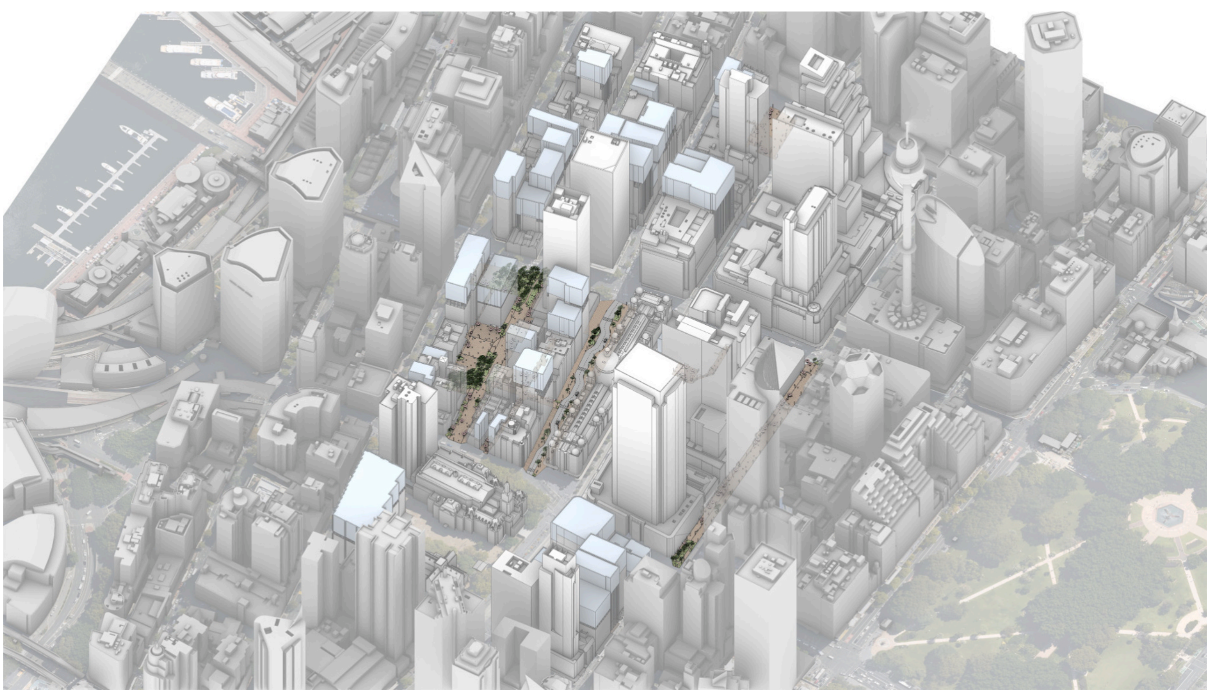

Fig. 19. Selected solution with the floor space added to existing buildings highlighted. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

selected to become trees or low-level plants.

With these metrics established, and their targets based on their defined qualitative trait, each solution created was assessed based on its ability to reach these target numbers with a maximum deviation of 10 %. As a solution approached the target percentage the metric moved closer towards zero, which, because the MOEA's aim was to minimise, was therefore a more optimal solution. Each metric received a weight depending on its perceived importance to the optimal solution, and the metrics were added together to give an overall score for the corresponding trait (ambience, beauty, comfort or safety). The MOEA's used this score and control of the variables to create an optimal solution for each qualitative urban trait.

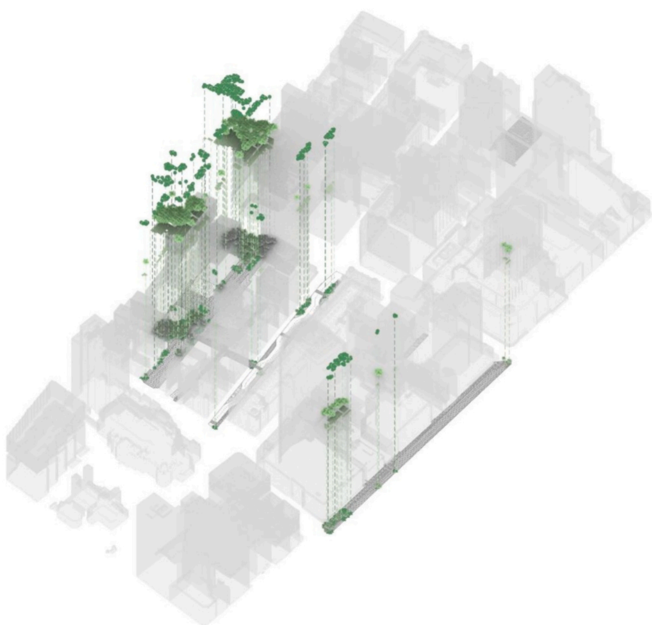

Fig. 20. Location and distribution of vegetation in the urban proposal.

4. Results

4.1. MOEA results

Through the definition of qualitative traits using multiple granular qualitative metrics, the MOEA generated optimised solutions that converged very successfully. The algorithm was run for 100 generations, with each generation having 50 individual solutions, resulting in a total of 5000 solutions over a simulation runtime of approximately 10 h. The settings used in the NSGA-2 algorithm are presented in Table 2. Fig. 11 showcases a subset of solutions extracted from the first evolved generation, presenting the variation between solutions created by the algorithm as it starts its exploration of the design space.

As can be observed in Figs. 12 and 13, the MOEA outputs converged to a subset of varied solutions approximately midway through the simulation run. This is shown through the movement of the standard deviation's (SD) bell curves to the left from the first (red) to the last (blue) generation of solutions. The width of the curve represents the amount of variation between solutions in a given generation; the more variation, the wider the curve and vice versa. As the solutions converge to a smaller, optimised collection of solutions, the curve becomes narrower and taller. This is supported by the fitness values chart, showing the same generations as line graphs that move downwards as the fitness values for each solution decrease towards the target of zero. The mean value trendline displays convergence in the simulation's runtime through the reduction levelling of the trendline's curve (Fig. 12). Finally, despite all four fitness objectives (qualitative traits) converging towards an optimal subset of the population, the parallel coordinate plot confirms that the four objectives remain in conflict (Fig. 13).

4.2. Selection mechanism

Of the 5000 solutions, a percentage were quantifiably better than others based on their fitness value for each fitness objective; these solutions are located on what is known as the Pareto front. As the total number of Pareto front solutions is typically too large for reliable analysis of each design option, the total pool of Pareto front solutions is filtered down to a more manageable size. To ensure variation is maintained when filtering the Pareto front solutions, the filtered solution pool includes four key solution types (Showkatbakhsh & Makki, 2022):

- the fittest solution for each fitness objective;
- the solution closest to the 'ideal' non-existent solution (should the objective not have been in conflict) known as the Utopia Point solution;
- the solution with equal ranking for all fitness objectives; and finally
- the Pareto front solutions clustered (using a hierarchical clustering algorithm with a K value of 18), with the centre of each cluster being selected to be part of the filtered pool of solutions.

This resulted in 25 solutions for further analysis (Fig. 14). This filtration of solutions from an original population of 5000 to a subset of 25 may seem extreme, but the subset retains the greatest amount of variation within the fittest solutions of the population (i.e. the Pareto front).

An initial visual analysis of the 25 solutions reflects the data presented in the analysis charts (Figs. 12 and 13), which is that the algorithm was successful in converging the population towards a solution set with similar geometric characteristics. However, despite being visually similar, there are in fact granular differences between these solutions, thus requiring an equally granular mechanism to further analyse the solutions and select a single optimal one.

The first layer of the selection mechanism was the extraction of each

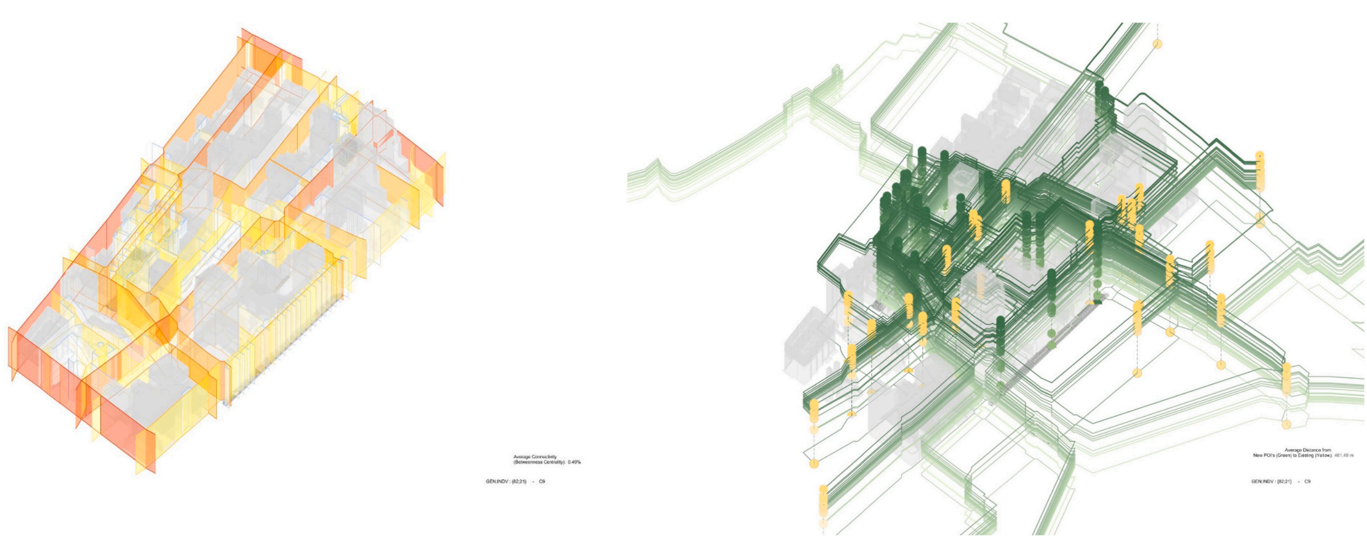

Fig. 21. Left: Betweenness Centrality analysis of the selected solution (average connectivity 49 %). Right: Paths between existing and new points of interest.

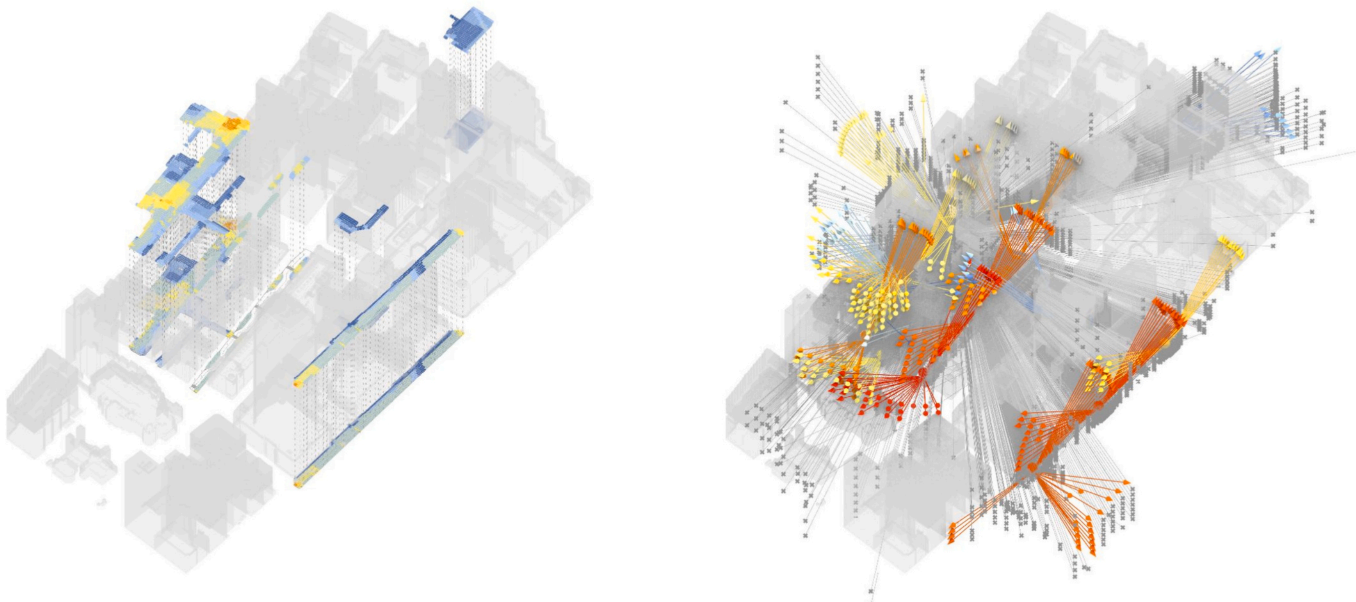

Fig. 22. Left: Solar analysis on street level (red to blue = most to least sunlight). Right: skyviews from focus points (red to blue = most to least visibility). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

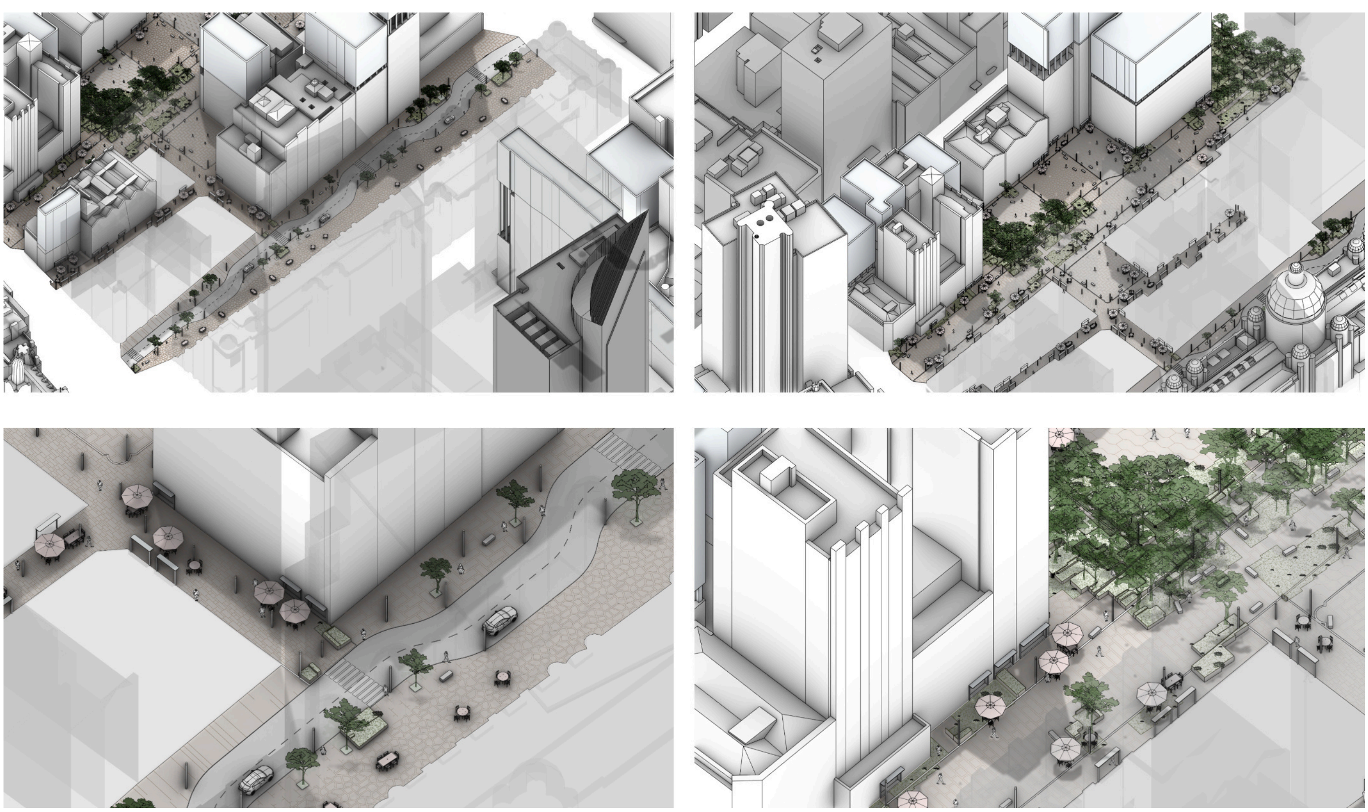

Fig. 23. Focused snapshots of the various urban elements in the selected solution.

qualitative metric from its combined score, allowing for the analysis of each metric as originally executed in the phenotype; these qualitative metrics formed the first layer of phenotypic indicators used to select a solution. In addition to these nine primary qualitative metrics, secondary metrics (Fig. 15) were integrated into the phenotypic indicators for further analysis of the granular differences between solutions.

The phenotypic indicators were categorised into larger groups – Visibility, Accessibility, Environmental, Solar and Urban – for ease of analysis. Each metric was calculated for each solution, the highest metric converted to a score of 1 and the lowest to zero, and all other metrics scaled accordingly.

Each phenotypic indicator scores the various solutions and is then weighted by its importance in the selection process (in this experiment, all primary metrics received a weight of 2, and secondary metrics

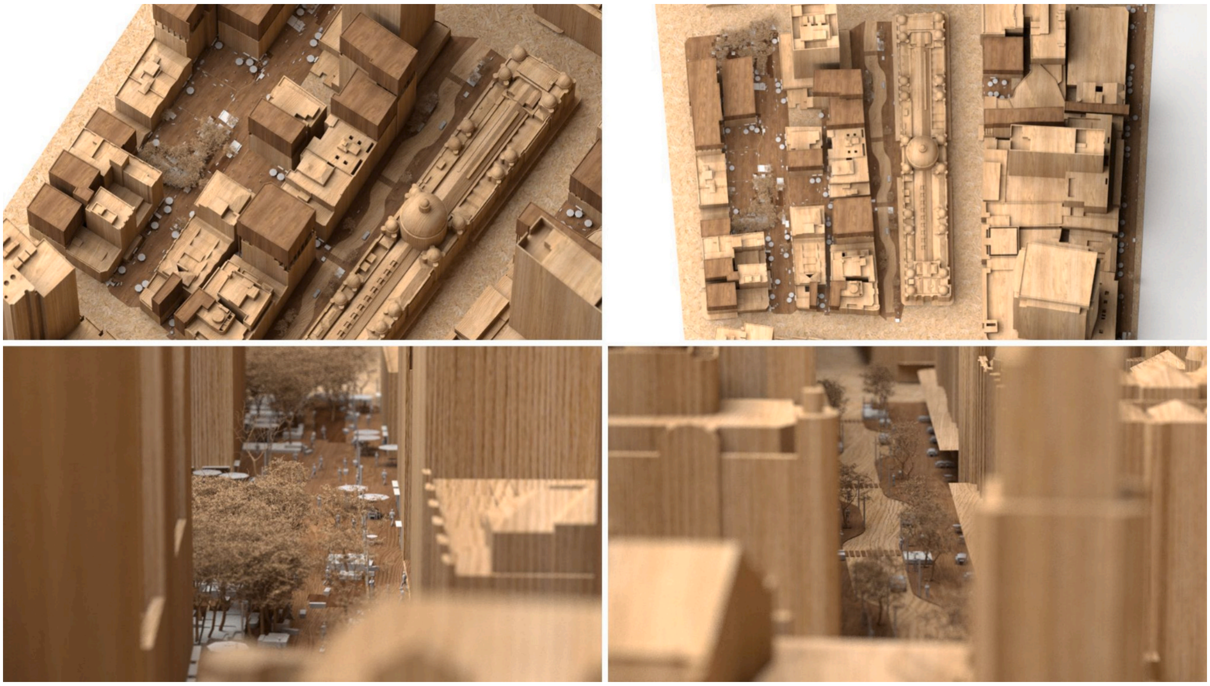

Fig. 24. Physical model visualisation of the selected solution.

received a weight of 1). The solutions' total scores (the sum of the weighted scores for all metrics) were normalised (0 to 1) and the top 10 % (scores above 0.9) selected (Table 3).

4.3. Selected solution

The top 5 solutions were compared and further evaluated. This second round of evaluation included a reformulation of the weighting criteria for each urban metric, allowing for a much more nuanced analysis and assessment of the remaining solutions (Table 4). As a result, the highest-scoring solution from this second round was identified as Gen.82;Ind.21, thus becoming the selected design solution from the experiment (Fig. 16).

Gen.82;Ind.21 scored highly on beauty, was best for all accessibility metrics, second best for skyview, and scored highly on all other phenotypic indicators. Additionally, this solution provided opportunities to connect various urban elements through road reconfigurations, such as connecting the pedestrianised portion of Pitt Street with an additional pedestrianised portion to its south.

5. Analysis

Because the MOEA converged the evolved population towards an optimal subset of solutions, the qualitative aspects of the top 5 solutions were only marginally different; all were viable final designs. Therefore, secondary metrics (visibility, accessibility and connectivity, environment, solar gain and urban condition) were required to differentiate urban quality. They were analysed in tandem with the primary qualitative metrics (skyview, low-level greenery, trees, seating, shading, facade activation, modern building facades, traditional building facades, and ground material variation). The re-ranking of solutions, and the performance of accessibility and connectivity, in particular, enabled identification of Gen.82;Ind.21 as the final solution.

Comparing the final selected solution to the current conditions of the site demonstrates the success of the generative process. The analysis methods for the primary qualitative metrics were used to analyse the existing site. Spaces occurring in both the existing site and Gen.82;Ind.21, such as the Town Hall Square, George Street and the pedestrian portion of Pitt Street, were omitted to allow for a more direct comparison. Subsequently, it was obvious that the existing Town Hall site has much less open plaza and green space than the proposed design (Fig. 17).

The existing site's qualitative traits were analysed in the same way as for the generated solutions, creating manually calculated fitness values. The fitness values for each trait were then integrated into the list of all solutions generated by the algorithm, allowing for the existing solution to compared directly to Gen.82;Ind.21. The existing solution was in the 30th percentile for ambience, 33rd percentile for beauty, 38th percentile for comfort, and 44th percentile for safety. In comparison, Gen.82;Ind.21 was in the 92nd percentile for ambience, 99th percentile for beauty (the best possible score), the 95th percentile for comfort, and the 92nd percentile for safety.

From a visual standpoint, the proposed redesign of Town Hall would greatly improve its public domain. Gen.82;Ind.21 facilitates multiple urban conditions that coincide with the overall improvement of the urban qualities of the site. In particular, the MOEA tended towards pedestrianising roads adjacent to the QVB, and selected the most adjacent road to maintain as mixed use, allowing for urban factors such as public transport and service access to be maintained in a pedestrian-friendly manner. Gen.82;Ind.21 involves two additional pedestrianised roads, one connected to newly introduced plazas and open spaces, and the other to the adjacent pedestrian portion of Pitt Street. As a result, Gen.82;Ind.21 creates a cohesive flow of public spaces in the dense urban fabric without compromising the flow of vehicular traffic through this segment of Town Hall. In creating this connected series of open spaces in the centre of the site, Gen.82;Ind.21 increases green space and vegetation cover dramatically. It establishes a diversity of spaces with unique qualities – narrow, publicly activated alleyways, shaded green spaces, and open thoroughfares that connect multiple points of interest (Fig. 18).

Additionally, the proposal to introduce additional volumes atop eligible buildings allows for the overall density of the site to increase. The design introduces volumes double of those removed evenly across the retained buildings (shown in blue), thereby factoring future growth in real estate availability into the design methodology (Fig. 19).

Gen.82;Ind.21's improvements to the existing site include an

Fig. 25. The process of using ai (stable diffusion) to convert a sketch extracted from the 3d model to the final render used for visualisation.

Fig. 26. Three examples of the ai process, with the shortlist of three renders displayed next to the final collaged image.

additional 2305.44 square metres of green space, allowing for approximately 170 additional trees and much new low-level flora (Fig. 20).

With the introduction of pedestrian-only "roads" in Gen.82;Ind.21, more pedestrian crossings on the mixed-use road and additional paths through open spaces, the overall connectivity of the area is improved, as an analysis of betweenness centrality (Fig. 21) shows.

Coinciding with Gen.82;Ind.21's increased green space is increased solar access throughout the site. Due to the density of tall buildings, many existing Town Hall streets receive little direct sunlight. The placement of green spaces throughout Gen.82;Ind.21 relies on areas with relatively high solar gain, as visual analysis of the redesigned site shows (Fig. 22).

Gen.82;Ind.21 was the statistically best solution with respect to the qualitative and survey data. The proposed method enables the proposed design's improvement to the overall quality of the site to be identified numerically (Figs. 23 and 24).

6. Visualisation

6.1. AI-assisted visualisation

The emergence of AI visualisation technology has revolutionised many industries, including design and architecture, unlocking new possibilities for visualising and conceptualising design ideas (Mirbabaie et al., 2022). Although controversial in its ability to replace human resources and dampen innovation (Van Laar et al., 2017), this technology empowers architects and designers to create immersive and realistic visual representations of their projects with unprecedented ease, as long as the approach to the utilisation of the AI technology is within the control of the user, and that it is used as a supporting tool that interacts and prompts greater creativity and innovation on the user's end (Santana & Díaz-Fernández, 2023). The accelerated design process provided by the AI visualisation technology also allows for the exploration of multiple iterations within a reduced time frame, and offers added value through increased interaction with the design by means of converting simple inputs such as sketches into design concepts. This technology is utilised in the final stages of the generative phase of this research, to examine its effectiveness in its ability to translate design ideas between designer and client, and as a medium for further innovation and idea generation.

Through the use of the Open-Source AI Image Generation system Stable Diffusion, a series of views were captured using traditional digital architectural methods. With the selected solution 3D modelled, the views were captured in various display methods, such as perspectival linework. These images were then input into Stable Diffusion's ControlNet interface in addition to text prompts to guide the AI to generate the desired outcomes. The process of image generation is carried out multiple times, as the system is still unpredictable. Through the use of ControlNet and the linework image, the geometries of the generated images remain consistent with the actual design.

The generative process is capable of creating a high yield of images in a short amount of time. For example, in the span of an hour over 30 images using the same view were created, each with varying degrees of success. The images are then filtered down based on preference for

Fig. 27. different interpretations of the same initial sketch rendered by two ai visualisers.

particular elements in each and traditional architectural methods of collaging multiple images together creates a final outcome which communicates the desired qualities of the space (Figs. 25 and 26).

The process of creating these visualisations was carried out multiple times, and to further explore the process different interpretations of the qualitative concepts was considered by having different visualisers generating images based on the same starting reference. In doing so the significance of generating a series of images and collaging the results into a single final image is emphasised, as through this process two different people, with different interpretations of the quantified qualitative data can reach final images that share the same spatial qualities (Fig. 27).

6.2. Comparison to existing sites

As part of the initial analysis of the image survey results, the highest and lowest ranked images (2 of each) identified by the survey results were further examined to better understand the colour distribution as well as brightness embedded within each location, the results of this analysis coupled with a more in-depth examination is the focus of study of future research by the authors. However, in an attempt to further understand the output form the AI visualisation, the results of this colour and brightness analysis were compared to the results of the same analysis conducted on the AI visualisations for the proposed model.

The two reference images chosen to compare the new designs against were the highest ranked images, located in Martin Place and Darling Square. As can be observed, through the iterative process of AI generating a high yield of images, selecting the most desirable, and stitching their desired elements into a single final image, the proposed designs share extremely similar colour palettes as the reference images (Fig. 28), further demonstrating the correlation between the data that was collected to quantify quality, and its generative use for the design of new

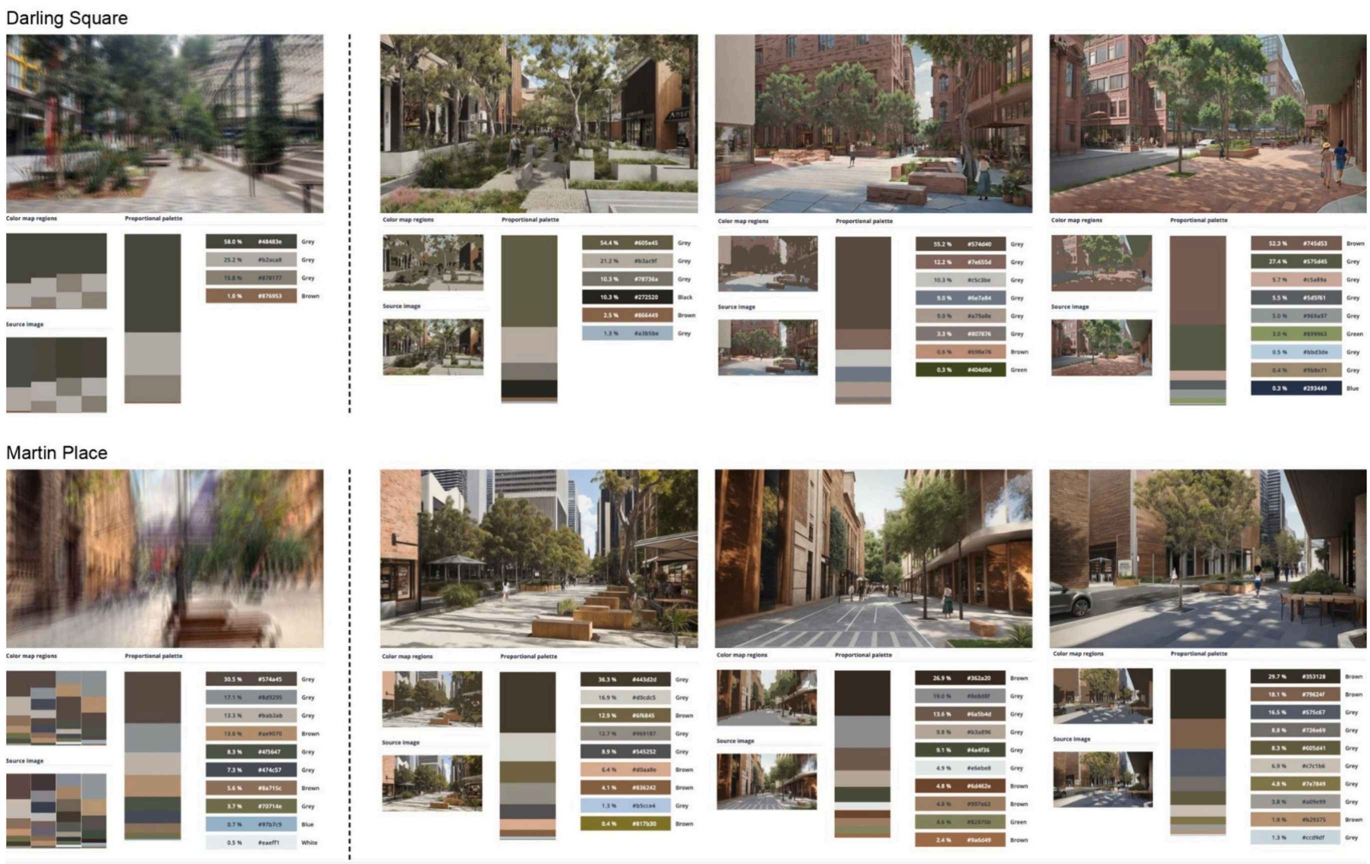

Fig. 28. Comparison of colour palettes of the selected solution (visualised through ai) to the highest ranked images from the survey. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

urban space.

Separate to this comparative analysis is a new typology introduced through the design process. The alley and laneway spaces identified in Town Hall's site were activated to the public through outdoor seating and dining space, and open storefronts. As this is a new typology, there were no survey images to effectively compare to; should this typology be implemented, the analysed image could be used as reference (Fig. 29).

7. Conclusions

The presented research makes part of a larger body of work that aims to provide a numerically driven approach to the quantification of urban quality. Where the first phase of the research collected data through subjective and objective input methods, in turn arriving at specific percentiles of urban metrics that define the four urban qualities of Ambience, Beauty, Safety and Comfort; the work presented herein examines the integration of these urban qualities (and more importantly, their numerical definition) in a generative design process that utilises a multi-objective evolutionary process, which is an algorithmic process that is inherently capable to solving design problems driven by numeric fitness functions. Therefore, the translation from quality to generative was highly facilitated by the use of a model that allows for this, in this case being a MOEA.

The model developed in the presented research uses the Sydney CBD as a case study, in which the problem of accessible and usable green space within a high-density environment plagues the CBD (and others worldwide). The presented design problem makes several hypothetical decisions, such as the removal of some buildings, the interchange of vehicular roads to pedestrian ones, and the addition of 'lost' space from building removal to existing buildings that have not been removed. However, despite being hypothetical, the underlying decisions are highly functional, and within the 30 to 50 year projection for urban redevelopment with the CBD. More importantly, the aim of the developed model is to demonstrate its highly adaptive capacity; different designers will approach the same design problem with a different set of variables, thus leading to a different design output, which is an option built into the developed model. However, key to the developed process is the optimisation of the urban proposal to the 4 urban traits listed above, using the same (or similar) percentile definition of each trait as per the data collected through the image survey. It is critical to highlight that should the survey have been conducted using images for another country, the percentile distribution of how each trait is defined would have likely differed, which in turn would have impacted the resulting design solution; however the process itself remains the same, thus presenting itself as model that can be adapted to suit different locations and design inputs, resulting in unique design solutions specific to the data inputted into the model.

The proposed method demonstrates the efficacy of complex simulations on qualitative models of the city, in a manner that can be adjusted to local conditions, external mitigating factors and various scales of implementation. The research analysis and development of interpretive models developed sequentially through site selection, multivariate qualitative model generation, analysis, and visualisation, each step producing distinct results, observations, and qualitative outcomes. Most importantly, what is developed is an adaptable model for integrating numerical representation of urban quality within a mostly automated generative process. As identified in the literature, there exists a wide range of methods to analyse and define urban quality; however, regardless of the method, if the qualitative analysis generates a quantifiable result, then it can be integrated within the design model presented in this paper. A detailed pseudo code of the design model is displayed in Fig. 30, identifying the different parts that can be modified

Fig. 29. The alleyway re-imagined. What was once a space for services, and inaccessible to the public is converted to an activated public space. The colour palette for this space does not correlate to the two reference images used in Fig. 27. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

by the user based on the data they have collected.

The research presents (and questions) the significance of the 2d image as a medium by which one can draw conclusions. There is no doubt to the significance of the 2d image as the primary format by which ideas are presented, either internally within design teams, or between designers and key stakeholders from the government and community. As such, the use of the 2d image may not be a full representation of the quality of space that is captured within the image, however it is considered as a fair representation to the overall quality one aims to achieve in the proposed space. Future steps in the research will aim to incorporate AR/VR to gain a better and clearer understanding of the spatial qualities generated through various design solutions; and it is expected that recent developments in AI, primarily image to video, will certainly streamline this process.

As work continues in this space, there are opportunities for continued development. These include the refinement of the methods by which some urban metrics are calculated, such as skyview or solar gain to factor in a higher granularity of obstructions by trees. Moreover, as it currently stands, the ‘loop’ of the presented research remains open, as the community whose feedback originally dictated the data used in the research were not engaged by receiving their feedback on the image results. This could be achieved through restarting the survey and including within it the AI visualisations generated and analysing how the images were ranked by the respondents, and if indeed they ranked them highly compared to other images. Most importantly, there is a danger of the presented method generating urban design solutions that fall in the ‘generic’, in which the individuality of urban space is lost due to the algorithm's ‘compliance’ with the required metrics that define each qualitative trait. Further research is required to ensure the peculiarity and uniqueness of urban spaces is retained, and somehow embedded as a design goal within the presented model.

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CRediT authorship contribution statement

Mohammed Makki: Writing – review & editing, Writing – original

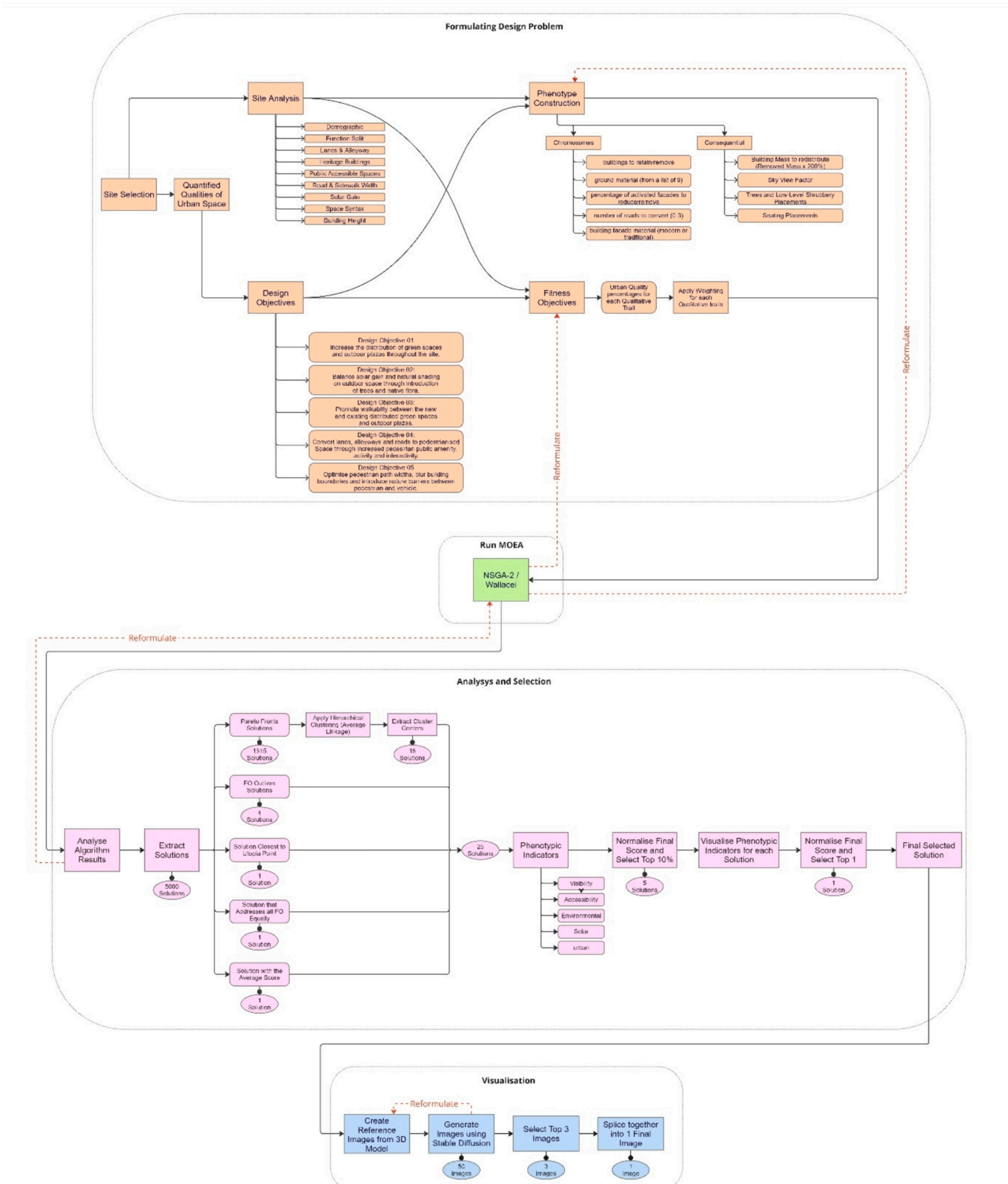

Fig. 30. Detailed pseudo code of the presented research. One of the key contributions of this work is the adaptability of the developed model. The model can be applied to a different site, phenotype, fitness objectives, or quantified qualities; allowing for significant flexibility in its application for alternative scenarios. The colour code used in this figure mirrors the same colour code used to represent the four steps of the developed model (presented in Fig. 6). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jordan Mathers:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Linda Matthews:** Writing – review & editing, Visualization, Methodology, Formal analysis, Data curation. **James Melsom:** Writing – review & editing, Investigation, Formal analysis. **Nimish Biloria:** Writing – review & editing, Investigation, Formal analysis. **Blake Raymond:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation. **Jacky Cheung:** Writing – original draft, Visualization, Validation, Investigation, Data curation. **Kim Ricafort:** Writing – review & editing, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Mohammed Makki reports financial support was provided by SJB. Mohammed Makki reports financial support was provided by Australian Government. Jordan Mathers reports a relationship with SJB that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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