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Willingness to pay for well-being housing attributes driven by design layout: Evidence from Hong Kong

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ABSTRACT

Housing design layout plays a crucial role in occupant well-being, yet existing research has not clearly understood occupants' preferences for different housing design layout attributes. This study aims to elucidate preferences by measuring demand-side willingness to pay (WTP) for housing attributes related to well-being and influenced by design layout. We first simulate the metrics of five housing attributes under different layouts, i.e., spatial daylight autonomy (sDA), spatial glare autonomy (sGA), natural ventilation effectiveness (NVE), predicted mean vote (PMV), and energy use intensity (EUI). Then, WTP for these attributes is disentangled from housing prices using the hedonic model. The findings demonstrate that a 1 % increase in sDA, sGA, and NVE corresponds to respective increases of 1.342 %, 0.694 %, and 2.842 % in housing prices, showing that residents value greatly the presence of natural ventilation and well-lit spaces with appropriate daylight. However, no significant correlations are found for PMV and EUI, suggesting a lack of a general preference towards thermal comfort or energy consumption in the Hong Kong context. This study contributes to a deeper knowledge of key well-being attributes in housing design as well as practical insights to create housing environments that prioritise occupant well-being and enhance market value. Future research should consider expanding to diverse housing markets, incorporating more well-being attributes, and examining the temporal variations of WTP.

1. Introduction

We shape our buildings; thereafter they shape us.

Winston Churchill

Improving well-being for a fulfilling, satisfying life is a fundamental lifelong pursuit [1]. A relatively subjective concept, well-being concerns how we perceive our surroundings and evaluate our own health, happiness, and contentment, both physical and mental. A sound sense of well-being can boost physical health, increase life expectancy, strengthen social relationships, and enhance productivity, and is influenced by many factors, including education [2], employment [3] and, not least of all, housing [4].

Given that humans spend a significant amount (approximately up to 90 %) of time indoors [5], the housing environment has a profound impact on well-being through a multi-sensory combination of visual, thermal, auditory, and olfactory senses [6]. Poor housing experiences can contribute to physical and psychological ill health, a notable example of which is sick building syndrome, a chronic illness caused by improper aerodynamic planning or inadequate air cleaning, which improves or disappears when individuals leave the building [7]. A clearer understanding of the impact of housing attributes therefore provides great opportunities to improve well-being.

Housing is a sophisticated product encompassing numerous attributes that affect the well-being of occupants, such as decorative aesthetics, living convenience, and design layout. In particular, design layout plays a significant role in driving human behaviour and emotions by influencing factors such as natural light, air ventilation, thermal comfort, and energy use [8,9]. Unlike interior decoration, housing layout is fixed. Therefore, designers should consider the well-being attributes of layout from the very beginning of the design phase. Buyers or renters are usually willing to pay a higher premium for design layout-driven attributes [10]. For example, in the northern hemisphere, a south-facing house tends to be more expensive than a north-facing house, indicating a preference for natural sunlight [11]. For housing design that generates more value and liveability, therefore, it is necessary to understand buyers' or renters' preferences for different attributes from the demand-side perspective.

Willingness to pay (WTP) is a powerful tool for characterising, quantifying, and monetising such demand-side preferences, as people are motivated to spend real money on goods or services they prefer.

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Nomenclature

AC	Air conditioning
ACH	Air changes per hour
ACH_{avail}	Available air changes per hour
ACH_{req}	Required air changes per hour
Adj. R^2	Adjusted coefficient of determination
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
A_z	Zone floor area
C_p	Specific heat
$\boldsymbol{D}$	Vector containing other hedonic attributes
DA	Daylight autonomy
DGP	Daylight glare probability
EUI	Energy use intensity
f_{cl}	Ratio of man's surface area while clothed
GA	Glare autonomy
GH	Grasshopper
HB	Honeybee
h_c	Convective heat transfer coefficient
HKUARPI	The University of Hong Kong All Residential Price Index
i	ith housing unit
j	jth estate
k	kth district
LB	Ladybug
LEED	Leadership in Energy and Environmental Design
M	Metabolic rate
NVE	Natural ventilation effectiveness
P	Housing price
p_a	Partial water vapour pressure
PMV	Predicted mean vote
P_z	Zone population
R_a	Outdoor airflow rate required per unit area
RH	Rhinoceros
R_p	Outdoor airflow rate required per person
sDA	Spatial daylight autonomy
sGA	Spatial glare autonomy
t	Time
t_a	Air temperature
t_{cl}	Surface temperature of clothing
$\overline{t_r}$	Mean radiant temperature
$\dot{V}$	Airflow rate
V_{bz}	Required ventilation rate
VIF	Variance inflation factor
vol	Room volume
WTP	Willingness to pay
ε	Error term of the regression
λ	Thermal conductivity
ρ	Density
τ	Regional fixed effects

Given the benefits to occupants' well-being of housing units that possess favourable layout attributes, there exists a higher WTP for these housing units among potential buyers or renters. Consequently, different well-being attributes are reflected in housing transaction prices. To isolate the WTP for various attributes from the overall housing price, the hedonic model can be employed to decompose the price into its constituent characteristics, such as natural light attributes and ventilation attributes [12]. By using this model, we can estimate the marginal WTP for specific layout attributes and determine their impact on the overall transaction price of a housing unit, providing a reference point for new building design. However, research on the estimation of WTP for well-being attributes driven by housing design layout remains scarce.

The aim of this study is to gain a better understanding of demand-side preferences for well-being housing attributes driven by design layout. It does so by simulating the values of housing attributes under different layouts and disentangling the WTP from housing transaction prices with the hedonic model. The remainder of this paper is structured as follows. Section 2 provides background information on well-being housing attributes and WTP in the housing market. Section 3 describes the methodology used in this study and Section 4 the results obtained. The findings and their implications for policymakers and developers are discussed in Section 5, and Section 6 draws our conclusions.

2. Background

2.1. Well-being attributes related to the housing environment

Well-being has gained increasing attention in recent housing research. Although there is no universally agreed definition of well-being, it generally encompasses physical, mental, social, and economic aspects of human life [13]. Understanding of well-being can be subdivided into hedonic theories (focusing on outcomes that make people feel good) and eudemonic theories (focusing on meaning, purpose, autonomy, self-acceptance, and so on) [4,14]. In this study, we prioritise hedonic theory because it aligns with the intention of diverse attributes to promote one outcome, i.e., increased occupant satisfaction with the built environment. Therefore, we define well-being as "the condition of mind that expresses complete satisfaction with the housing environment, rather than merely the absence of disease or infirmity" [6,15].

The housing environment plays a significant role in shaping our overall quality of life by influencing our senses, including sight, sound, touch, and feel. Existing studies have identified a plethora of attributes that impact well-being [16,17], which can be broadly classified into two categories (see Fig. 1). Neighbourhood attributes relate to the characteristics of the adjacent area where a house resides, including traffic conditions [18], access to amenities [19], access to green space [20], and sociodemographic characteristics [21], among others. Housing attributes, on the other hand, are intrinsic attributes of the house itself and are not related to the characteristics of the surrounding area. Salient examples of housing attributes include design layout [17], structural safety [22], and watertightness [16], all of which contribute to well-being. Neighbourhood attributes are largely determined by site location, while housing attributes, particularly layout, are significantly influenced by design.

On examination of design layout, it becomes obvious that it affects people's well-being by influencing the physical environment. For example, proper ventilation induced by a well-planned layout can help reduce indoor pollutant levels and condition temperature and humidity levels [23], while a south-facing house (in the northern hemisphere) can be exposed to plenty of natural light providing circadian stimulus [24]. Favourable layout designs can improve the thermal comfort of the occupants, eliciting higher morale, health, and productivity [25]. Moreover, energy-efficient layouts can simultaneously yield environmental, economic, physical and psychological benefits by reducing overall energy consumption [26,27].

Layout design is intricate, requiring a sequence of sophisticated decisions to balance various incompatible goals, such as the need for more sunlight and also a cooler environment. However, there have been few investigations of occupants' preference for these different attributes. To inform layout design, it is thus essential to understand the occupants'

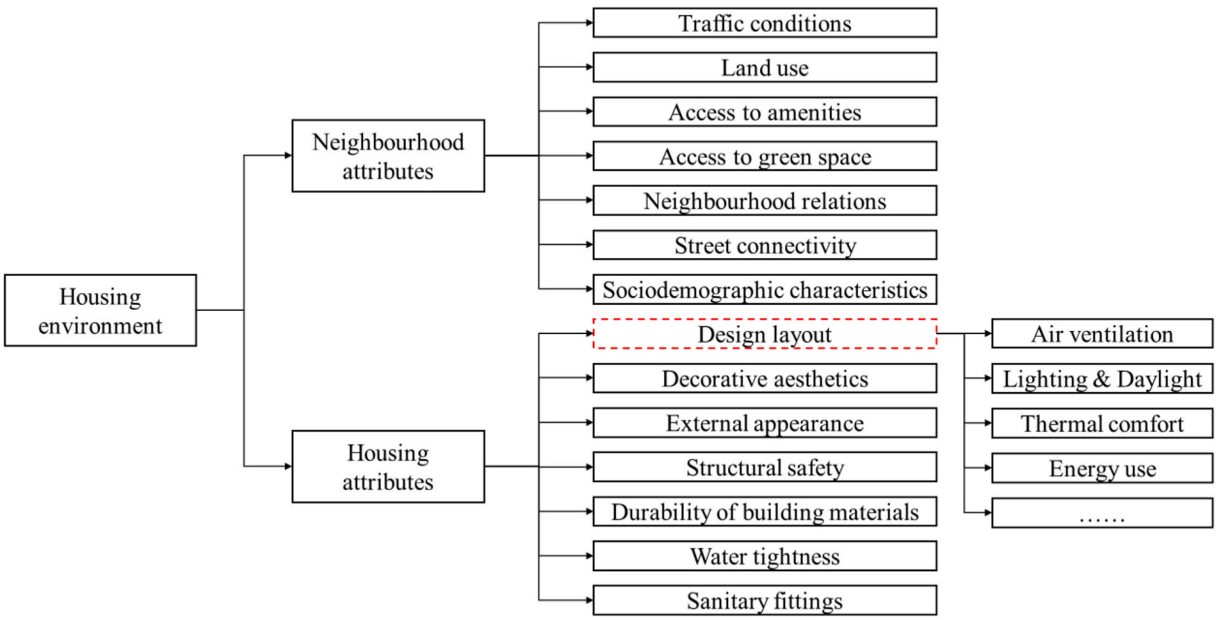


Fig. 1. Attributes influencing well-being in the housing environment.

preferences for various well-being attributes, so that human expectations can be incorporated into the design and development of housing to create better living spaces.

2.2. Willingness to pay (WTP) in the housing market

Willingness to pay (WTP) refers to the maximum amount of money an individual is willing to pay for a particular good or service [28]. In the context of the housing market, WTP plays a crucial role in understanding occupant preferences, housing affordability, and market dynamics. When measuring WTP, Breidert et al. [29] summarised two types of methods: *revealed preference* and *stated preference*, as shown in Fig. 2. Revealed preference methods utilize observed choices and market behavior to infer WTP indirectly. For example, hedonic pricing models are commonly used to estimate the implicit marginal prices of energy efficiency by analysing actual market transactions [30]. For the stated preference methods, survey-based approaches are adopted in a direct or indirect way [31]. The former involves directly asking individuals how much they are willing to pay, while the latter elicits WTP by examining individuals' ranking of products with different attributes.

Numerous factors affect an individual's housing WTP, in addition to the neighbourhood attributes and housing attributes we mentioned in the previous section, as well as some external market influences. For neighbourhood attributes, existing studies have explored the WTP for public transportation [18], clean air [32], green space [20], adjacent amenities [33], etc. Meanwhile, several housing attributes also exert an impact on people's WTP, and research in this area investigates energy consumption efficiency [33], sustainable housing [10], seismic retrofitting [22], information technology facilities [34], etc. Market conditions including supply and demand dynamics, interest rates, and housing market cycles also influence WTP [35,36]. While the literature on WTP in the housing market has made significant contributions, there still exist limitations. WTP, as an indicator of user preferences for well-being attributes induced by design layout, has been little examined in the literature.

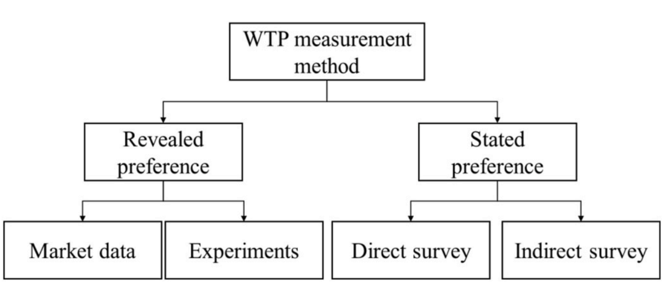


Fig. 2. Taxonomy of methods measuring willingness to pay (WTP).

3. Methodology

The adopted methodology can be divided into three steps. Firstly, housing transactional data, e.g., price, housing layout, and location, are collected and sampled. Secondly, 3D models of selected housing units are manually created and exploited for performance analysis of various well-being housing attributes. Finally, the obtained performances are used to regress them on the housing transaction prices using the hedonic model.

3.1. Data collection

Data collection was conducted within the context of Hong Kong for two primary reasons. Firstly, Hong Kong's real estate market has developed into a relatively stable system with well-established regulations and transparent information disclosure, ensuring that housing is traded fairly and efficiently [37]. This provides a suitable environment for investigating genuine WTP as reflected in transaction prices. Secondly, the well-being attributes of housing in Hong Kong vary widely, with a significant number of high-end homes tailored to higher income levels, as well as a large population living in cramped housing conditions [38]. This diverse range of well-being housing attributes to investigate allows for a comprehensive understanding of demand-side preferences.

Fig. 3 shows the flowchart for data collection. We began by obtaining the full list of 511 major housing estates, meaning residential buildings constructed by a single public or private developer with a minimum of 3000 residents or 1000 domestic households [39]. Then, a random sampling technique was employed to select ten estates across major residential areas in Hong Kong, as shown in Fig. 4. Next, the

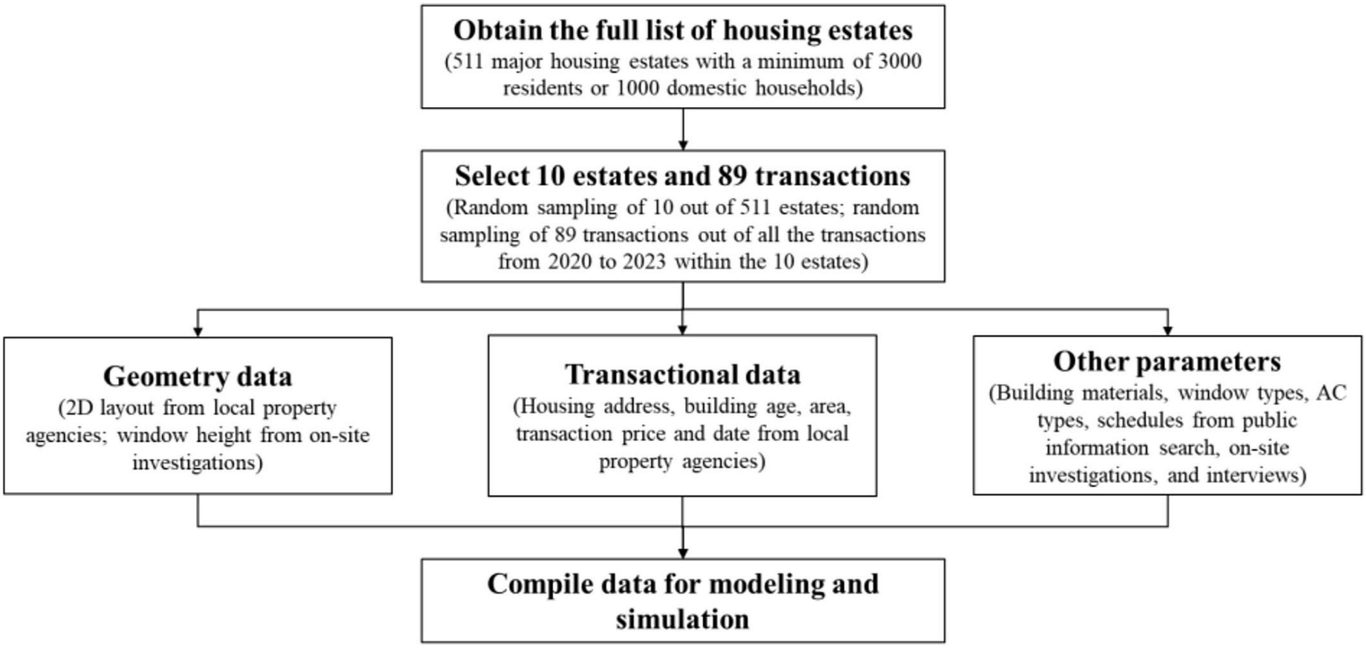


Fig. 3. Flowchart for data collection.

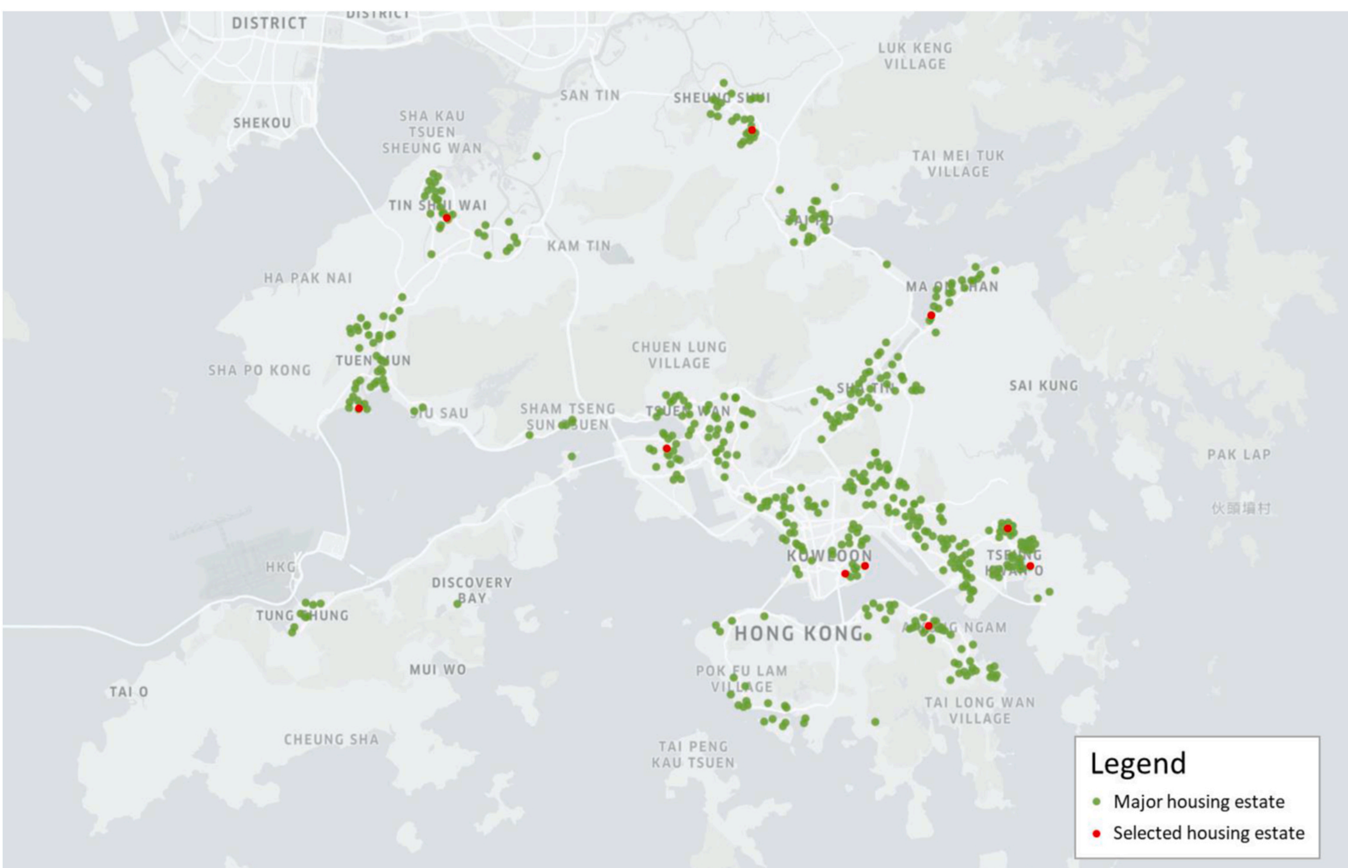


Fig. 4. Distribution of major housing estates in Hong Kong.

transactional data of the selected major estates, ranging from 2020 to 2023, were collected from local property agencies. These data include housing address, building age, area, 2D layout, transaction price and date. Even though we randomly sampled the estates, the resulting number of transactions of these selected estates was still too large for subsequent analysis, i.e., modeling the 3D housing environment. Therefore, another round of random sampling was performed for these transactions. In total, we selected 89 representative housing transactions across ten housing estates, ensuring even coverage of different types of housing units in Hong Kong. This enabled a robust analysis of WTP for different attributes of housing units and how these preferences vary across the population.

We need to collect additional parameters for more accurate 3D modeling and simulation of 89 housing units across 10 selected estates. This includes data on building materials (material type, dimensions, physical properties), window height, window types (side hung, top hung, or end-slider), and air conditioning (AC) systems (split-type AC or window-type AC). We conducted a public information search, complemented by on-site investigations of the building exterior and interviews with homeowners, property managers, and real estate agents. Given that each estate was developed by a single developer, the initial building materials are typically uniform. However, considering the age range of 5–30 years, variations due to renovations and modifications by new homeowners are expected. Complete interior inspections being impractical, we relied on photographic evidence from real estate transactions which are publicly available real estate websites. These photos helped infer the current materials used, offering a reasonable approximation of each housing unit's material state, despite potential limitations in capturing every detail.

Various schedules were determined by incorporating Hong Kong's social conditions. It is worth noting that average household schedules were adopted as a housing unit is not occupied by a specific household all the time. Moreover, by keeping all other factors consistent, including schedules, we had the opportunity to examine the impact of the design layout. Using the approach proposed by Yu et al. [40], we categorized the population into working adults, non-employed adults, and children. Working adults are typically out on weekdays from 8:00 to 18:00, children from 8:00 to 17:00 for school, taking into account commuting, work, shopping, etc., while non-employed adults are home most of the time, spending only 30 % of their time outside for social, exercise, and learning activities. On weekends, all groups spend 70 % of their time at home. Bedtime is uniformly assumed as 22:00–6:00 daily. Lighting is considered active when occupants are present and natural light is insufficient. AC is assumed operational during occupancy and when temperatures exceed the cooling set point. Based on the statistics from [41], Hong Kong's population is 7,413,070 with an average household size of 2.7, including 10.9 % children (0–14 years), 53.2 % working adults, and 18.9 % non-employed adults, which are calculated using a labour force participation rate of 59.7 %. The generated average schedules, illustrating occupants' behavioral patterns, is presented in Fig. 5.

3.2. Simulation

3.2.1. Simulation procedure

We circumvented a lack of quantitative data on housing attributes, e.g., daylight and ventilation, by simulation. The Rhinoceros (RH) 3D software and Grasshopper (GH) tool equipped with various plugins, including Ladybug (LB), Honeybee (HB) and EnergyPlus extension, were utilized to execute the simulation and derive specific metrics for housing attributes (Fig. 6). The simulation comprises three steps (Fig. 7).

1) *Parameter input.* These parameters include building type, building age, structure type, building materials (e.g., thermal properties and density), and room schedule (e.g., occupancy schedule, lighting schedule, electrical equipment schedules). gives an example of the details regarding the use of building materials in Taikoo City, i.e., one of the housing estates of interest.

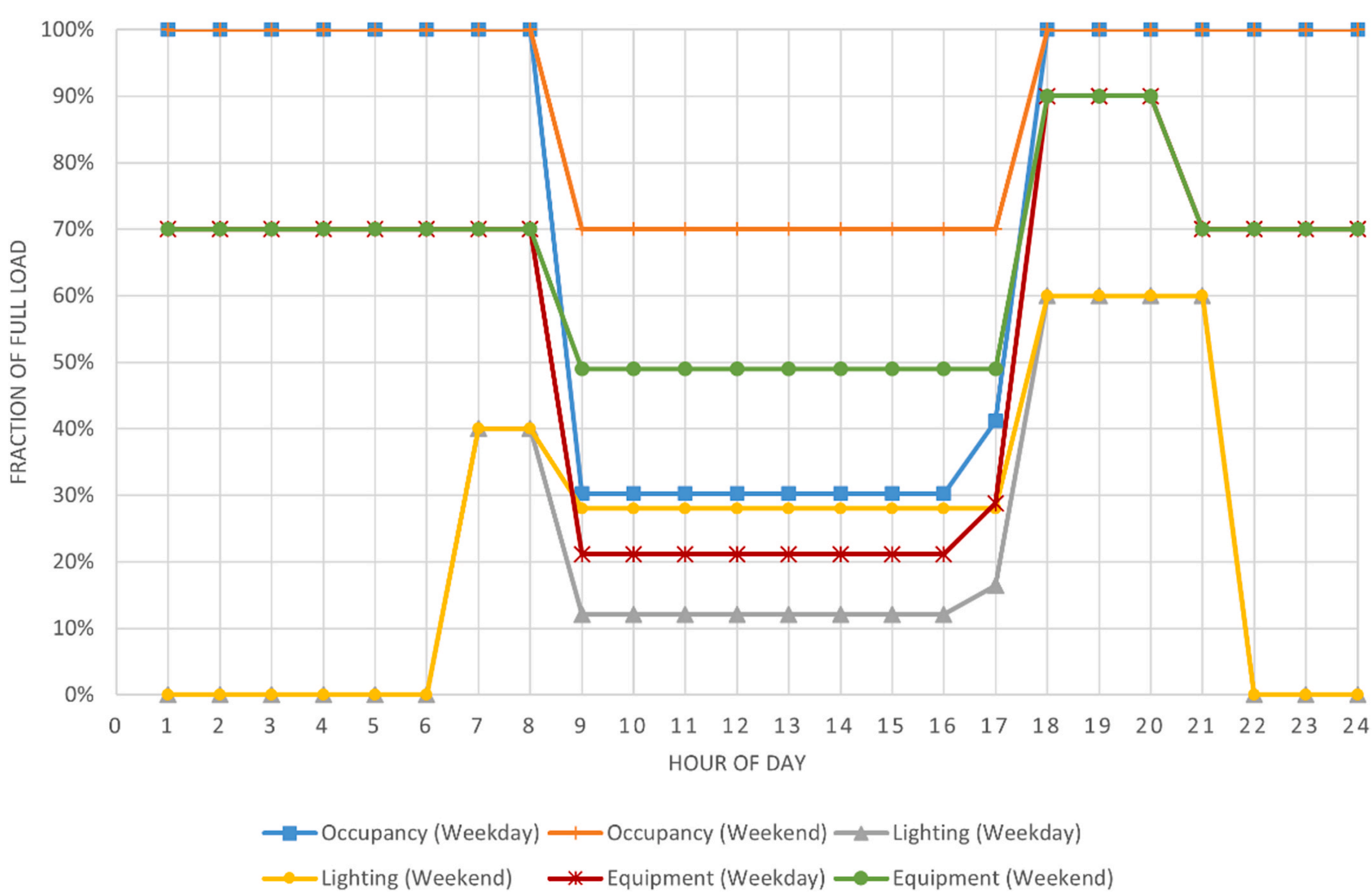


Fig. 5. Weekday and weekend schedule data.

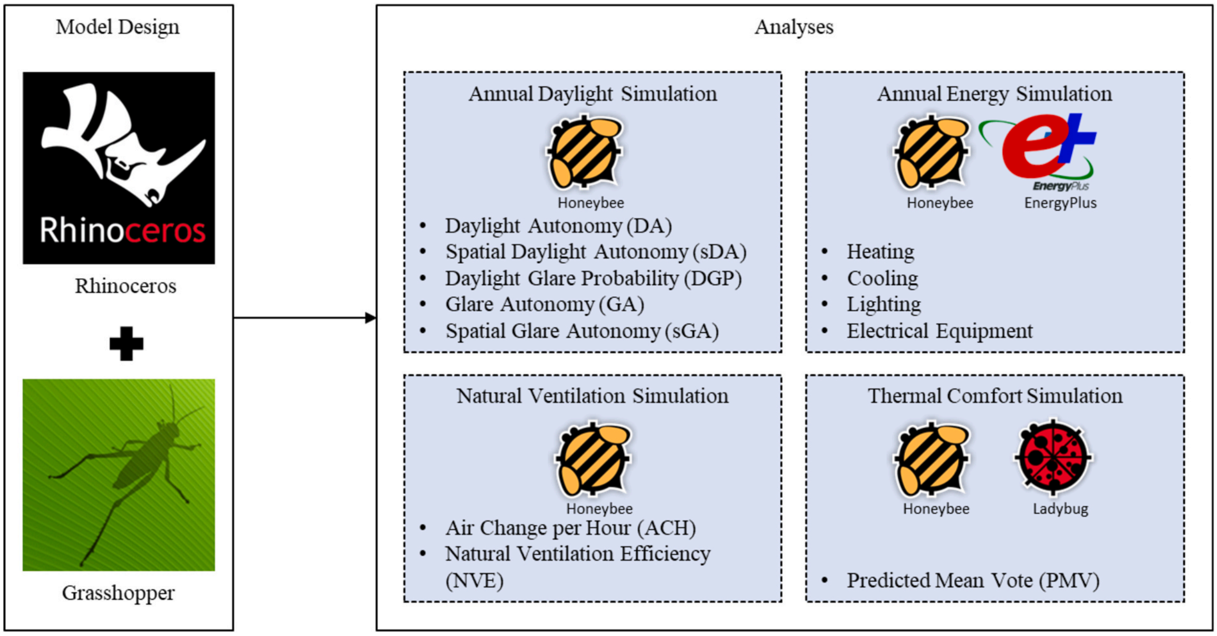


Fig. 6. Software for simulating different housing attributes.

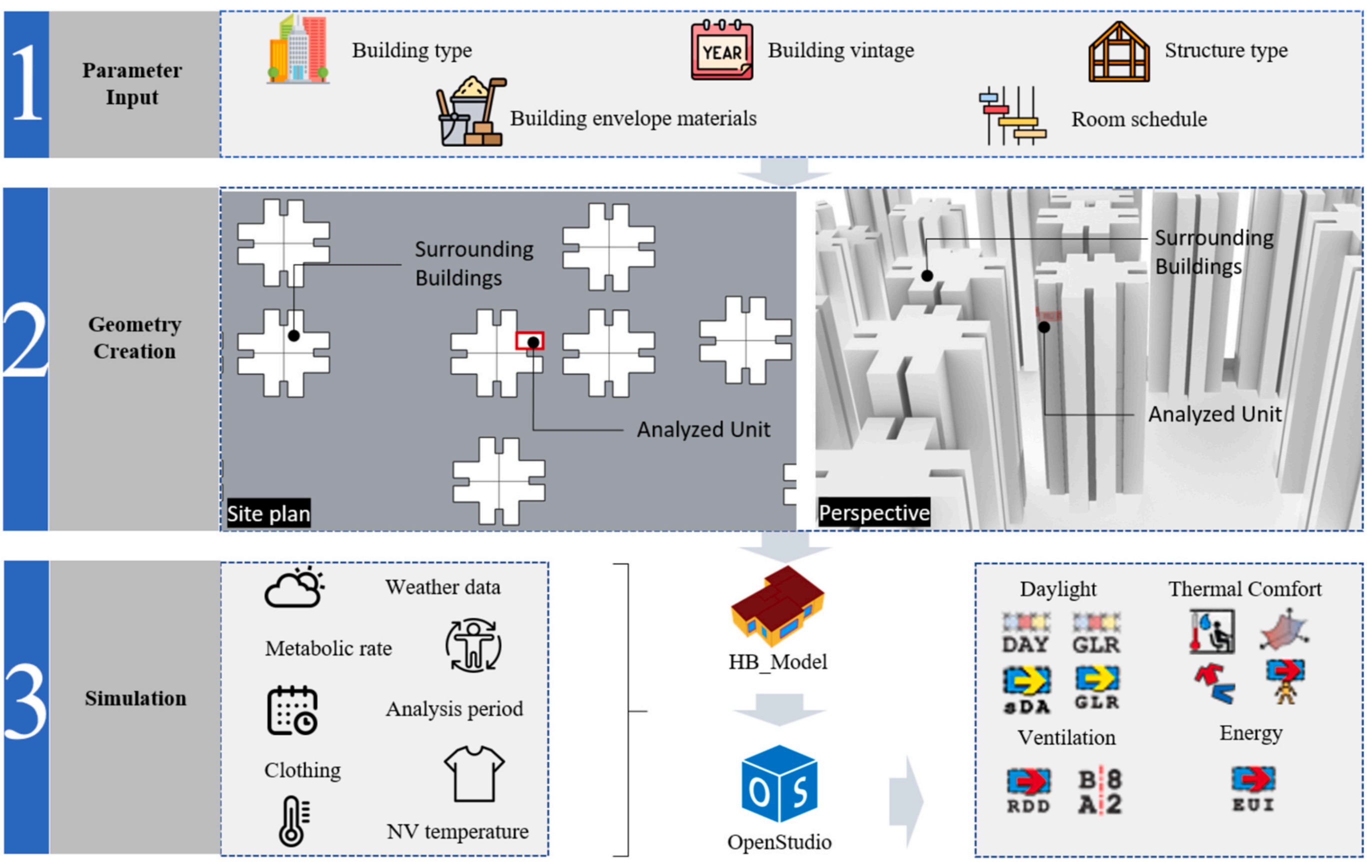


Fig. 7. Three-step simulation procedure.

2) Geometry creation. The target housing units need to be finely modelled with interior space division and layouts. Therefore, based on the collected 2D floor plans and the data measured from on-site investigations, we used RH and GH to create the 3D fine model as shown in Fig. 8. In our modeling approach, the window's horizontal length and position are derived from 2D floor plans, while its height is obtained from on-site measurements, collectively enabling precise window modeling. The cross-sectional area for air exchange was then calculated based on the window type and its maximum opening angle. For side hung and top hung windows, we assumed maximum opening angles of 45 and 30°, respectively [42]. The cross-sectional area was calculated accordingly. For end-slider windows, the area was considered as either

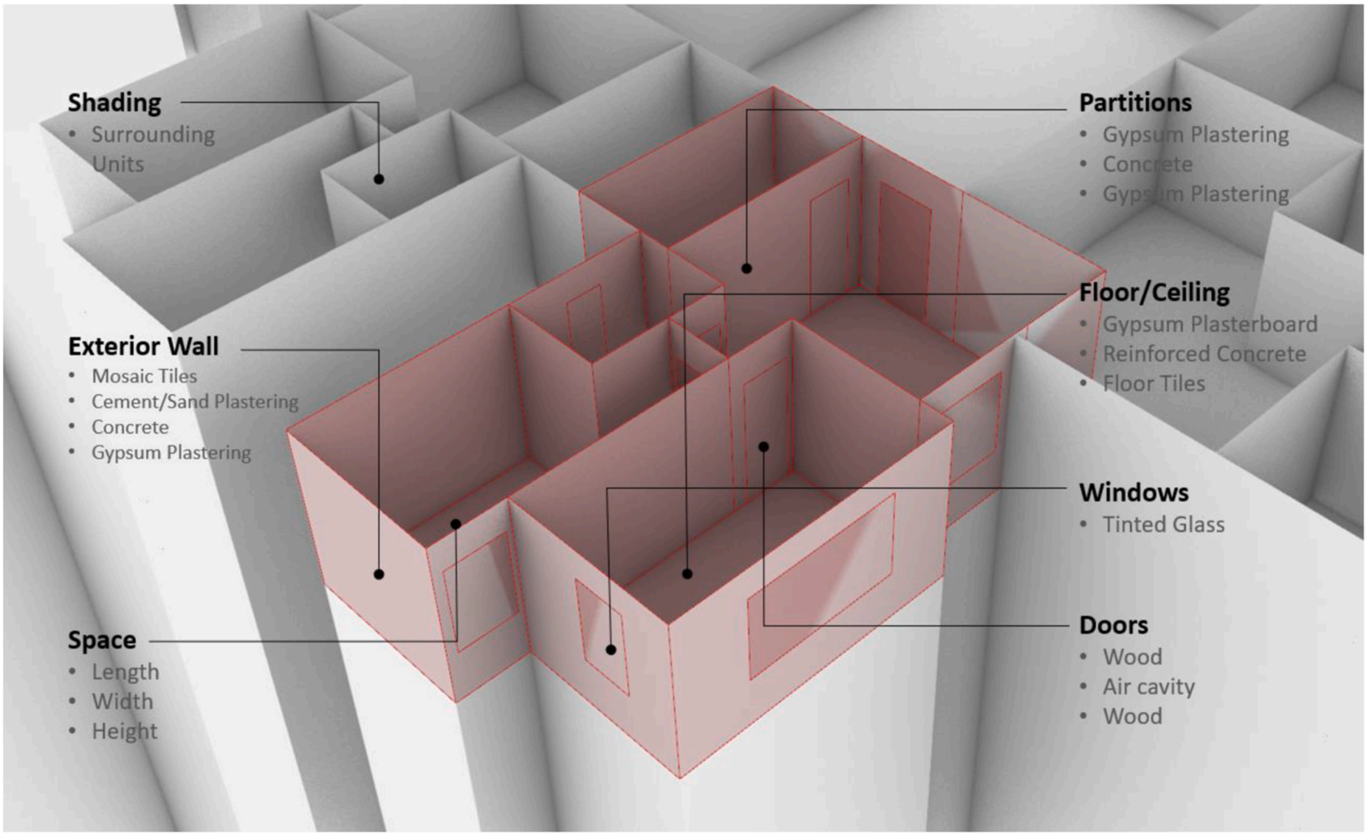


Fig. 8. Fine 3D model of the housing unit.

full or half of the window area, depending on whether they were fully or partially open. Windows were assumed to have a visible transmittance of 0.881, a solar heat gain coefficient of 0.775, and a U-value of 5.78 W/m^{2}K [43]. Moreover, the surroundings can affect the building performance and must be modelled and involved in the simulation. To factor in the influence of surrounding buildings, we downloaded rough 3D models of buildings within approximately 1 km^2 around the target building from Cadmapper (https://cadmapper.com/). Although these models lacked internal details, their external shapes were sufficient to simulate the shading effects on the target building. The optical characteristics of surrounding buildings in the simulation were carefully configured using an opaque radiance modifier. Parameters set included diffuse reflectance at 0.45, specular reflectance at 0.05, and roughness at 0.1.

3) Simulation. The simulation settings were tailored to the Hong Kong context, including local weather conditions (sourced from EnergyPlus weather data available online, covering temperature, humidity, wind speed, etc.), natural ventilation cooling temperature set at 22 °C, and mechanical cooling temperature set at 26 °C. The coefficients of performance for split-type AC and window-type AC were configured as 2.8 and 2.4, respectively [44]. The metabolic rate and body surface area in housing scenarios of occupants were set to 1.2 met and 1.8 m^2 [45]. Parameters regarding lighting and equipment were informed by the survey from Yu et al. [40]. The power density for a standard light fixture is approximately 40 W, and each room in the simulated models was assumed to be equipped with one such light fixture. Additionally, the total average energy consumption for household equipment was estimated at 4.76 kWh per day. To run the energy simulation through EnergyPlus, the HB models with the target and surrounding buildings were translated into OpenStudio Model files. We simulated the visual comfort by HB Annual Daylight models and HB Annual Glare models, thermal comfort by LB Predicted Mean Vote Comfort models, ventilation by natural ventilation effectiveness models, and energy consumption by HB Energy Use Intensity models.

3.2.2. Evaluation metrics

This section describes the quantitative metrics for each housing attribute.

(1) Daylight

Natural daylight utilisation increases the health and productivity of the users, yet the amount of daylight entering the room should not exceed the limit where it would cause glare for occupants [46]. In this study, two daylight metrics are used.

Spatial Daylight Autonomy (sDA): This metric, presenting the spatial feature of Daylight Autonomy (DA), is defined by the Illuminating Engineering Society of North America's Daylight Metrics Committee [47] as "the per cent of an analysis area that meets a minimum daylight illuminance level for a specified fraction of the operating hours per year." Higher sDA indicates larger areas possessing quality daylight [48]. The minimum illuminance level was set to 300 lux for Leadership in Energy and Environmental Design (LEED) certification for at least 50 % of the analysis period [49]. We focus on not only the amount of indoor obtained natural daylight, but also the glare it may cause.

Spatial Glare Autonomy (sGA): This metric, signifying the spatial feature of Glare Autonomy (GA), is defined as the fraction of views in the space that achieves the set target that a maximum number of hours that Daylight Glare Probability (DGP) exceeds the given threshold [50]. The higher sGA a room gets, the less glare occupants will get in the room. In this study, the threshold for DGP was set to 40 % and the maximum number of hours was set to 5 % of occupied hours.

(2) Natural ventilation

Natural ventilation can be evaluated by ***Natural Ventilation Effectiveness (NVE)***, a performance metric proposed by Yoon and Malkawi [51]. It is defined as the cooling capability of natural ventilation in a given space. It compares the actual hourly airflow rates and the ideal one that is required [52]. This metric is calculated as Eq. (1).

$$NVE = \frac{\sum \alpha}{n}\begin{cases} \alpha = 1, if\ ACH_{avail} \geq ACH_{req} \\ \alpha = 1, if\ ACH_{req} = 0 \\ \alpha = ACH_{avail}/ACH_{req}, otherwise, \end{cases} \tag{1}$$

where ACH_{avail} stands for the available air changes per hour (ACH) provided through apertures, ACH_{req} stands for the required ACH, and n is the total hours in the simulation period. The ACH_{avail} and ACH_{req} is calculated in Eq. (2)&3.

$$ACH_{avail} = \frac{3600(s)\dot{V}}{vol} \tag{2}$$

$$ACH_{req} = \frac{3600(s)V_{bz}}{vol} \tag{3}$$

where $\dot{V}$ is the airflow rate, vol is the room volume, and V_{bz} is the required ventilation rate suggested by [52], whose calculation is given by Eq. (4).

$$V_{bz} = R_p \times P_z + R_a \times A_z \tag{4}$$

where R_p is outdoor airflow rate required per person, P_z is zone population, R_a is outdoor airflow rate required per unit area, and A_z is zone floor area.

(3) *Thermal Comfort*

Predicted Mean Vote (PMV) is a thermal comfort model developed by Fanger [53], predicting the thermal sensation scale of occupants in an indoor environment, from −3 to +3, which means too cold to too hot [54]. The recommended PMV range for thermal comfort is between ±0.5 [53]. It is derived by comparing the heat balance between the actual heat flow from the human body in a given environment and the heat flow required to achieve optimum comfort at a specified activity [55,56]. It is calculated as Eq. (5).

$$\begin{aligned} PMV = &\left(0.303e^{-0.036M} + 0.028\right)\{(M - W) - 3.05 \times 10^{-3} \times [5733 \\ &- 6.99(M - W) - p_a] - 0.42 \times [(M - W) - 58.15] \\ &- 1.7 \times 10^{-5}M(5867 - p_a) \ - 0.0014M(34 - t_a) \\ &- 3.96 \times 10^{-8}f_{cl} \times \left[(t_{cl} + 273)^4 - (\overline{t_r} + 273)^4\right] - f_{cl}h_c(t_{cl} - t_a)\} \end{aligned} \tag{5}$$

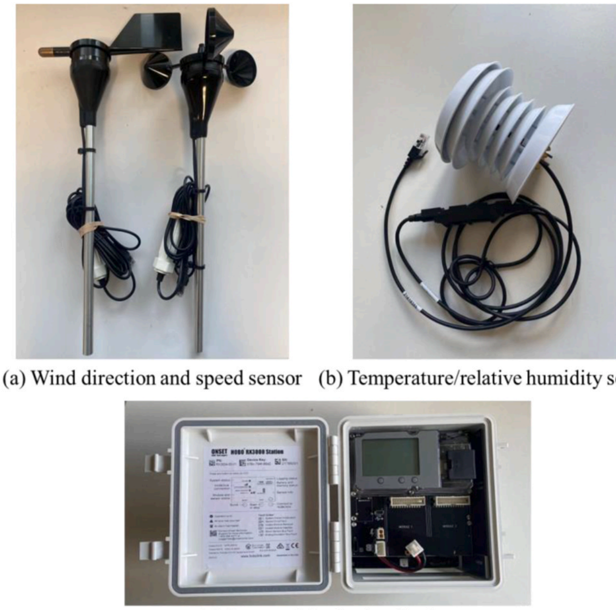
where M is the metabolic rate, W is the external work, f_{cl} is the ratio of man's surface area while clothed, t_a is the air temperature, $\overline{t_r}$ is the mean radiant temperature, p_a is the partial water vapour pressure, h_c is the convective heat transfer coefficient and t_{cl} is the surface temperature of clothing.

(4) Energy Consumption

Energy Use Intensity (EUI) is defined as the energy consumption for cooling, heating, lighting and electricity equipment of a building in a specific period [57]. It is reported in kilowatt-hours per square metre (kWh/m^2). The housing space is fully air-conditioned, and the cooling and heating set points were set at 26 °C and 22 °C, respectively.

3.2.3. *Simulation validation*

We selected seven housing units evenly distributed in Hong Kong and conducted simulations using the process depicted in Fig. 7. To maximize consistency between simulated and actual conditions, it is necessary to match outdoor weather conditions in simulations. We utilized time-series data from the Hong Kong Observatory [58], which provides detailed information on temperature, wind, solar radiation, etc., at granular intervals ranging from 1 to 10 min. Concurrently, field tests were performed for validation purposes. As shown in Fig. 9(a), we employed Wind Speed Sensor (S-WSB-MO03) and Wind Direction Sensor (S-WDA-MOO3), which were positioned as close as possible to the center of openings. The measured wind speed was multiplied with the cross-sectional area of the opening to obtain the airflow rate, which was then further taken into Eq. (2) to calculate the ACH_{avail}. With the obtained ACH_{avail}, NVE was then calculated based on Eqs. (1)–(4). Fig. 9 (b) shows the Temperature/Relative Humidity Sensor (S-THC-MOO2) with solar radiation shield to improve the measurements in sun-exposed areas. The measured wind speed, temperature, and humidity were then utilized to calculate the PMV value according to Eq. (5). In addition, Fig. 9(c) shows an RX3000 Remote Monitoring Station, which is used to log the measured field data. By comparing the simulation results with the actual field data collected over a week, we observed differences of 7%–18 % and 10%–21 % for NVE and PMV, respectively, indicating the reliability of the simulation outputs.



(a) Wind direction and speed sensor (b) Temperature/relative humidity sensor

(c) Remote Monitoring Station

Fig. 9. Field measurement equipment for wind, temperature, and humidity.

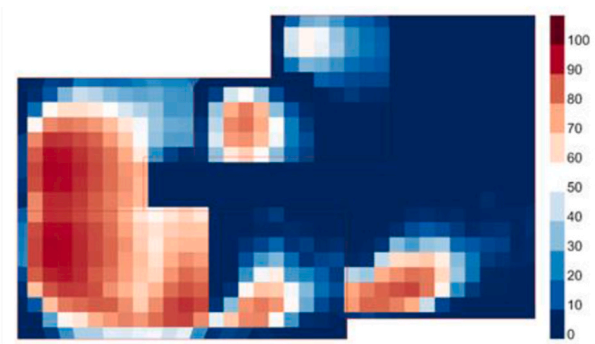
3.3. *Regression model*

In this study, we employed the hedonic model to examine the WTP relationship between housing prices and well-being housing attributes, namely daylight, ventilation, thermal comfort, and energy consumption. The hedonic model, first articulated by Rosen [59], is a revealed-preference method used in economics and urban studies to determine the factors that contribute to the price of a good. In our case, the good of interest is the residential housing unit. We used the common logarithmic model specification for the following reasons [60]. Firstly, applying a logarithmic transformation often results in a distribution that is closer to normal. Secondly, the transformation allows us to use a linear model to estimate non-linear relationships effectively. Thirdly, the economic meaning of the estimated coefficients is better explained in terms of elasticity. A 1 % change in an independent variable can be directly associated with a β% change in the dependent variable (e.g., house prices), where β represents the regression coefficient. The regression model is illustrated as Eq. (6):

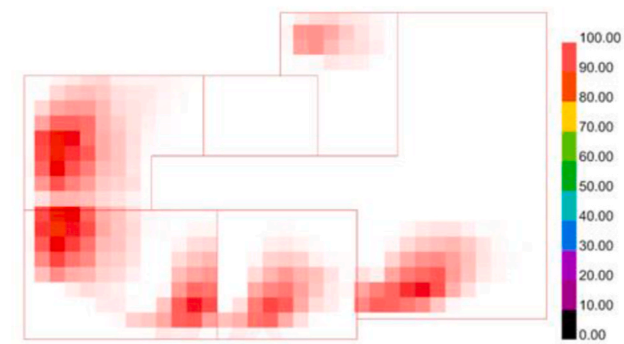
$$ln\ P_{ijkt} = \alpha + \beta_1 lnsDA_i + \beta_2\ ln\ sGA_i + \beta_3\ ln\ NVE_i + \beta_4\ ln|PMV_i| + \beta_5 lnEUI_i + \gamma \boldsymbol{D}_i + hkuarpi_t + \tau_k + \varepsilon_{ijkt} \tag{6}$$

where the variables of interest are explained below:

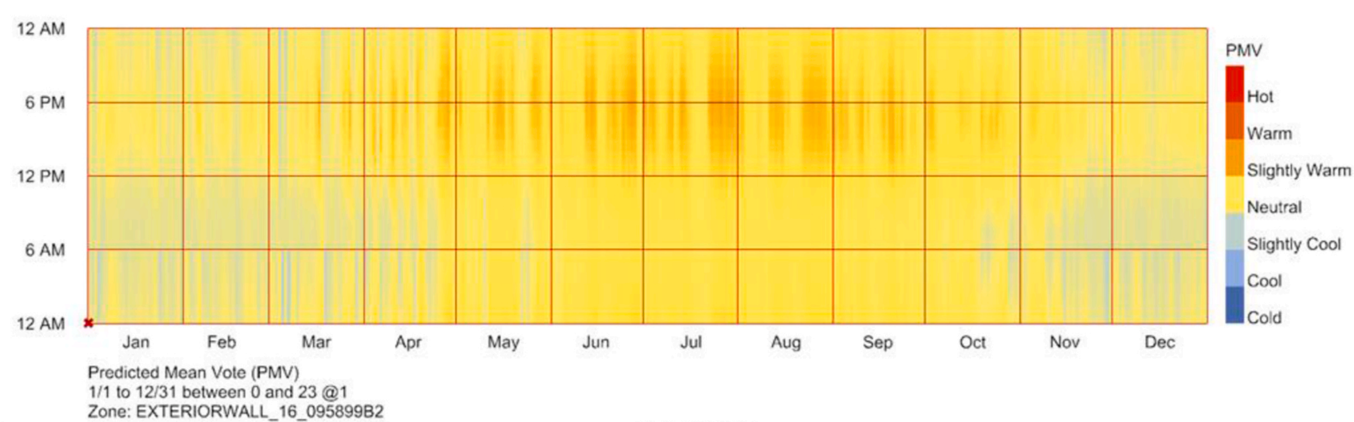
P_{ijkt}: housing price of the housing unit i located in estate j and district k at time t;
sDA_i,sGA_i,NVE_i,PMV_i,EUI_i: metrics for evaluating housing attributes;
$\boldsymbol{D}_i$: vector containing other hedonic attributes, including building age, area, and floor number;
$hkuarpi_t$: The University of Hong Kong All Residential Price Index (HKUARPI) developed by Chau [61], which is calculated based on repeat sales and therefore merely captures price fluctuations caused by market factors (e.g., overall macroeconomic conditions, monetary policies), rather than by hedonic attributes of a housing unit;
τ_k: regional fixed effects at the district level, whereby the "districts" are the 18 districts defined by the Home Affairs Department [62]. The fixed effect is a method to control for time-invariant unobserved individual characteristics that can be correlated with the observed independent variables, eliminating the omitted variable biases. This regional fixed effect term accounts for the housing price premium due to unobserved location factors, e.g., transportation convenience, amenities, access to green, schools and medical facilities;
ε_{ijkt}: error term of the regression



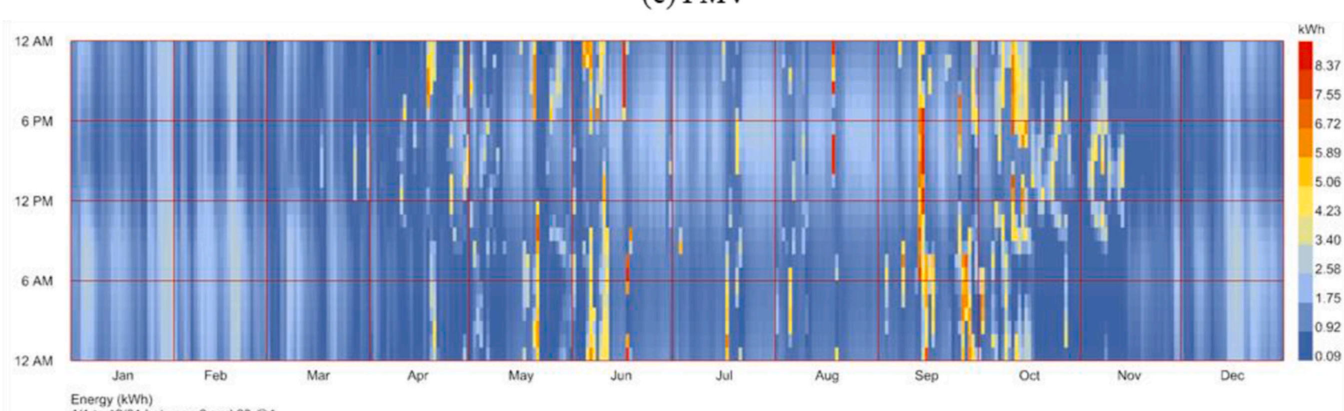
(a) sDA



(b) sGA



(c) PMV



(d) EUI (Total Energy)

Fig. 10. Simulation results of a typical design layout.

4. Results

4.1. Simulation results

Fig. 10 provides a visualization of the simulation results for various housing attributes, excluding the ventilation metric. Fig. 10(a) and (b) depict the results of the daylight and glare simulation, respectively. These results highlight the significant correlation between the lighting conditions and design aspects such as layout and size of the windows. The final values of sDA and sGA for the subsequent regression can be obtained by averaging the simulated daily values. Fig. 10(c) illustrates the PMV values, providing insights into the thermal comfort levels of the housing units over the course of a simulation year. The visualization clearly indicates a tendency towards the warmer side most of the time, which is in line with the typical climate conditions experienced in Hong Kong. Similarly, the PMV values for regression were averaged using the daily PMV values from simulation. In Fig. 10(d), the presented data illustrates the total energy usage throughout a simulation year. The EUI value for a housing unit can be calculated by summing the energy consumption of the heating, cooling, lighting, and electricity equipment, and then dividing it by the total area of the unit. The ventilation metric, namely NVE, is a numerical value expressed as a percentage that quantifies the ventilation effectiveness, therefore not visualised in Fig. 10. The average of the simulated daily NVE was used for the regression with house prices.

4.2. Regression results

Table 1Table 2 demonstrates the descriptive statistics of the main variables for 89 samples. The mean housing price is HK$10,960,380, with a standard deviation of HK$7,223,419. The mean floor level is approximately 20.69, while the mean age of the selected houses is around 26.60 years. The mean area is about 675.39 ft^2, with a standard deviation of 202.65 ft^2. For the two daylight-related variables, both sDA and sGA are measured on a scale from 0 to 1. They have a mean value of 0.44 and 0.83, respectively. For the variable NVE, it is recorded spanning from 0.24 to 0.29. The variable PMV, indicating thermal comfort performance, has a mean value of −0.061 with a standard deviation of 0.11. PMV is measured on a scale from −3 to +3. The last variable, namely EUI, has a mean value of 176.66 kWh/m^2, which matches well with the records from [63], i.e., approximately 163.5 kWh/m^2 for a typical Hong Kong residential housing unit.

Before regression, concerns regarding multicollinearity (e.g., potential correlation between floor number and daylight) need to be rigorously examined by conducting a Variance Inflation Factor (VIF) analysis. A VIF value exceeding 10 typically indicates high multicollinearity, warranting further investigation or methodological adjustments [64]. As shown in Table 3, our analysis revealed that all variables had VIF values significantly below the threshold of 10, suggesting that multicollinearity is not a substantial concern in this study.

Table 4 presents the results of the main regression analysis. It includes the coefficients and corresponding *t*-statistics for each variable included in the regression model. In Model 1, only three hedonic attributes are involved, i.e., age, area, and floor. The Adj. R^2 reaches 0.6661, although the relationship between building age and house prices is not statistically confirmed in this study. Both the area and floor are positively associated with housing prices at a high level of confidence, implying that higher and larger houses usually sell for a higher price.

Model 2 includes variables related to well-being housing attributes. These variables represent metrics for daylight (“ln_sDA” and “ln_sGA”), ventilation (“ln_NVE”), thermal comfort (“ln_PMV”), and energy use performance (“ln_EUI”). The inclusion of these variables significantly increases the Adj. R^2 to 0.8381. Amidst these variables, the coefficients for “ln_sDA”, “ln_sGA”, and “ln_NVE” are all statistically significant, indicating that these attributes have a strong positive effect on housing prices. This result suggests a willingness to pay a higher premium to meet the demand for daylight and ventilation. However, the coefficients for “ln_PMV” and “ln_EUI” are found to be not statistically significant, suggesting that these attributes do not have a significant impact on housing prices.

Model 3 involves additional variables that take into account the local spatial-temporal context. Temporally, changes in housing prices due to market volatility (e.g., local economic dynamics and loan interest rates) over time can be captured by the HKUARPI. The variable “hkuarpi” shows a coefficient of 0.00286, which is statistically significant at the 0.05 level ($p < 0.05$), indicating HKUARPI is positively related to housing prices. Spatially, by adding regional fixed effects, the model can obtain a more accurate estimate of the average effect of well-being housing attributes within each region, while controlling for any time-invariant differences between regions (e.g., transportation, amenities and medical facilities). Therefore, with the inclusion of the spatial-temporal context, the Adj. R^2 has further improved to 0.8447. In addition, such inclusion does not essentially affect the regression results for the well-being housing attributes (i.e., the coefficients for “ln_sDA”, “ln_sGA”, and “ln_NVE” remain statistically significant), exhibiting the robustness of these relationships to different specifications.

In the main regression results, the positive and significant coefficients are obtained for “ln_sDA,” “ln_sGA,” and “ln_NVE,” with values of 1.342, 0.694, and 2.842, respectively. Since we employed a logarithmic model, the economic interpretation suggests that a 1 % increase in sDA, sGA, and NVE would lead to a respective increase of 1.342 %, 0.694 %, and 2.842 % in housing prices. These coefficients represent the marginal WTP for these housing attributes by residents.

Notably, the highest marginal WTP is observed for NVE, indicating

Table 1
Building materials in Taikoo City.

Building component		Material	Thickness(m)	λ [W/(m·k)]	ρ (kg/m^3)	C_p [J/(kg·K)]
External Walls	Layer 1 (exterior)	Mosaic Tiles	0.005	1.5	2500	840
	Layer 2	Cement/Sand Plastering	0.013	0.72	1860	840
	Layer 3	Concrete	0.1	2.16	2400	840
	Layer 4 (interior)	Gypsum Plastering	0.013	0.38	1120	840
Interior partitions	Layer 1	Gypsum Plastering	0.013	0.38	1120	840
	Layer 2	Concrete	0.1	2.16	2400	840
	Layer 3	Gypsum Plastering	0.013	0.38	1120	840
Floor/Ceiling	Layer 1	Gypsum Plasterboard	0.01	0.38	1120	837
	Layer 2	Reinforced Concrete	0.18	1.9	2300	840
	Layer 3	Floor Tiles	0.01	0.8	1700	850
Windows	Layer 1	Tinted Glass	0.006	1.05	2500	840
Doors	Layer 1	Wood	0.06	0.16	800	2093
	Layer 2	Air cavity	0.038	0.025	1.293	1
	Layer 3	Wood	0.06	0.16	800	2093

Note: λ is thermal conductivity, ρ is density, and C_p is specific heat.

Table 2
Results of descriptive statistics of main variables.

Variable	Obs.	Mean	Std. dev.	Min	Max	Range	Unit
Price	89	10960380	7223419	2928000	37800000	[0, +∞)	HK$
Floor	89	20.68539	13.48113	1	53	[0, +∞)	/
Age	89	26.59551	6.213473	21	45	[0, +∞)	/
Area	89	675.3933	202.6527	401	1180	[0, +∞)	ft^2
sDA	89	0.443256	0.08745	0.304033	0.701282	[0, 1]	/
sGA	89	0.833527	0.099038	0.602767	1	[0, 1]	/
NVE	89	0.255039	0.011098	0.237487	0.290046	[0, 1]	/
PMV	89	−0.06103	0.108444	−0.20738	0.212871	[-3, +3]	/
EUI	89	176.6586	35.15850	112.5826	246.7512	[0, +∞)	kWh/m^2

Table 3
Results of the variance inflation factor analysis.

Variable	VIF	1/VIF
ln_sDA	2.96	0.337587
Area	2.88	0.346695
ln_NVE	2.86	0.34991
ln_EUI	1.79	0.558613
ln_PMV	1.69	0.592313
floor	1.57	0.63777
age	1.43	0.699857
hkuarpi	1.21	0.824893
ln_sGA	1.18	0.847781
Mean VIF	1.95	

Table 4
Main regression results.

	(1)	(2)	(3)
	ln_Price	ln_Price	ln_Price
Age	−0.00629	−0.00678	−0.00569
	(-1.09)	(-1.43)	(-0.60)
Area	0.00227***	0.000915***	0.000993***
	(12.92)	(4.48)	(4.98)
Floor	0.00824***	0.00196	0.00168
	(3.10)	(0.85)	(1.03)
ln_sDA		1.444***	1.342***
		(6.59)	(4.02)
ln_sGA		0.604***	0.694***
		(2.77)	(3.82)
ln_NVE		2.994***	2.842***
		(3.07)	(4.87)
ln_PMV		−0.0399	−0.0446
		(-0.58)	(-0.60)
ln_EUI		0.117	0.141
		(0.73)	(0.79)
hkuarpi			0.00286**
			(3.28)
N	89	89	89
Region fixed effects	No	No	Yes
R-squared	0.6774	0.8529	0.8606
Adj R-squared	0.6661	0.8381	0.8447
Root MSE	.33375	.23236	.22759

Note: t statistics in parentheses; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

that residents place a high value on natural ventilation in their rooms. This may be attributed to the high temperatures and humidity in Hong Kong, where natural ventilation serves as an effective remedy. The second highest WTP is for sDA, which specifically indicates the desire for more area with a daylight level of 300 lux. This finding aligns with the evidence that only a few rooms in Hong Kong receive sufficient sunlight due to poor housing conditions. Residents are willing to pay a higher premium to acquire a dwelling with adequate sunlight. Generally, a certain level of daylight intensity is desirable, rather than the higher, the better. Our study also found a positive correlation between sGA and house prices, suggesting that residents have an evident preference for avoiding glare-induced discomfort. On the other hand, there was no significant WTP observed for the thermal comfort and energy consumption housing attributes. One possible explanation could be that people may not have an intuitive understanding of thermal comfort performance and energy consumption at the time of home purchase.

5. Discussion

The process of selecting parameters for the simulation has been recognized as crucial for the accuracy and relevance of the results. For parameters intrinsic to the housing units, such as material properties and window sizes, the approach employed aims to replicate the actual conditions of the housing as accurately as possible. This replication has been facilitated through publicly available information, on-site investigations, interviews, and comparative analysis of photographs. A limitation, however, must be acknowledged: detailed access to each housing unit was not feasible, necessitating educated guesses about some internal conditions based on interviews and photographic evidence.

For occupant-specific parameters, average values reflecting the general occupancy patterns in Hong Kong have been adopted. This decision is informed by the understanding of the fluidity of occupancy in housing markets, where occupant preferences and behaviors can vary significantly. The objective here is not to replicate the performance of buildings under specific occupant conditions but to investigate the influence of layout-driven attributes. It is imperative for readers to recognize that such simulations, while providing valuable insights, may not fully correspond with actual usage scenarios. For example, while daylight simulation in controlled laboratory conditions may have minimal error, real-world applications can vary significantly due to occupant interactions and modifications, such as altering interior layouts or usage patterns of blinds and electric lighting. These factors can lead to discrepancies between predicted and actual performance, with daylight simulations potentially over-predicting real-world outcomes by 5–34 % [65]. Additionally, Yu et al. (2019) underscores the critical impact of occupant behavior on building energy consumption, showing that calibrating energy models with Post Occupancy Evaluation data, which more accurately reflects occupant behavior, can significantly enhance the accuracy of energy consumption predictions.

The recognition of well-being as a critical factor in housing research highlights the importance of understanding the various dimensions of well-being and their impact on the housing environment. In this regard, this study has made the following contributions. Firstly, it utilises WTP to neatly quantify and monetise the value of well-being housing attributes. By measuring the relationship between housing prices and these attributes, the study provides a straightforward and effective approach to understanding the economic implications of housing design and its impact on well-being.

Secondly, the WTP quantification can unleash the potential of generative design methodologies to enhance the quality and efficiency of architecture designs. The findings in this study can inform the weighting and optimization criteria within generative design algorithms. By iteratively refining and optimizing these designs based on

WTP, generative design enables the creation of highly tailored and user-centric solutions. Leveraging computational power, this iterative process not only improves the overall quality of the design but also enhances efficiency by automating and accelerating the design exploration and decision-making process [66].

Thirdly, the findings of this study have important implications for the housing supply side, particularly for developers, real estate professionals, and the government or policymakers. For developers and real estate professionals, identifying the well-being housing attributes with higher WTP can guide the development of more desirable and suitable housing options, leading to increased market value. Moreover, knowledge of WTP can empower the government or policymakers to make informed decisions regarding the allocation of resources, targeting subsidies or incentives to specific groups or areas, urban planning, and the provision of public goods and services. By enhancing the overall quality and appeal of residential developments, the government has the opportunity to attract more talents, increase tax revenue and promote sound urban development.

Lastly, the study also has significant benefits for the housing demand side, particularly for individuals seeking or investing in housing that promotes well-being. By learning the average WTP response in the market for different housing attributes, occupants can prioritise these attributes when searching for a new home based on their actual financial capabilities, thereby improving their overall well-being given a constrained budget.

This study has limitations. Firstly, the analysis was based on a specific dataset from a particular region, which may limit the generalizability of the findings to other contexts. Future studies are needed to compare the similarities and differences in the WTP patterns exhibited among different regions and interpret the causes. Secondly, the study focused on a selected set of well-being housing attributes, and there may be other relevant attributes that were not included in the analysis. Well-being is a broad concept that encompasses a variety of attributes with intricate relationships among them. Some of the attributes were selected mainly due to the ease with which we could simulate and quantify them. Future research should address how well-being can be measured more comprehensively. Thirdly, this study provides an estimate of WTP based on historical data. However, people's consumption behaviours are changing with social, economic, cultural, and environmental contexts. Therefore, future WTP is likely to be different from that of the past. Fourthly, the method employed in the simulation validation for obtaining ACH_{avail} only offers a simplified estimation. Lastly, only employing regional fixed effects to account for location-based differences may not sufficiently capture the nuanced impact of specific locational advantages, such as proximity to universities, subways, and hospitals. It is necessary to incorporate the detailed locational variables into the hedonic model.

6. Conclusions

Well-being has been increasingly discussed in housing and built environment research, indicating a growing recognition that housing goes beyond mere shelter and encompasses various factors that contribute to physical, mental, and social health. Housing design layout is an aspect that significantly affects occupants' well-being. This study contributes to the ongoing discourse on well-being by examining the willingness to pay (WTP) for housing attributes driven by design layout, i.e., daylight, ventilation, thermal comfort, and energy consumption. By using simulation techniques to obtain quantitative metrics of these housing attributes, we had the opportunity to employ the hedonic model to regress the relationship between each metric and housing prices and reveal the WTP for these attributes. Our regression analysis revealed that daylight and ventilation metrics such as sDA (spatial daylight autonomy), sGA (spatial glare autonomy), and NVE (natural ventilation effectiveness) had positive and significant coefficients. Specifically, a 1 % increase in sDA, sGA, and NVE corresponded to a respective increase of 1.342 %, 0.694 %, and 2.842 % in housing prices. This suggests that residents highly value natural ventilation and areas with appropriate daylight. However, a significant WTP was not found for thermal comfort and energy consumption metrics. This may indicate that these attributes are not currently perceived as significant factors influencing house prices in the studied context.

The findings of this study have far-reaching implications for various housing sector stakeholders. With an understanding of the attributes upon which individuals place a premium, such as natural ventilation and daylight, designers can incorporate these features with the aid of generative design algorithms to create high quality designs. Developers can also benefit by aligning their housing products with the demands of potential buyers or renters, increasing the value of the housing market. Policymakers can utilize the quantified WTP as valuable guidance in allocation of resources or subsidies for the poorly housed, urban renewal, and public house planning to enhance the overall well-being of the community. Moreover, knowledge about the value placed on specific attributes empowers individuals to evaluate and compare different housing options more effectively and prioritise features that align with their own preferences at the most economical prices.

Future research could be conducted in the following directions. Firstly, it is desired to expand the scope of the study to include a wider range of housing markets to enhance the robustness of the findings. Secondly, incorporating other relevant attributes under the umbrella of human well-being could further advance our understanding of the relationship between housing attributes and occupant well-being. Thirdly, future research endeavours should consider monitoring the dynamic nature of WTP for well-being housing attributes, as human preferences and priorities are subject to change over time. By addressing these avenues, future research can contribute to the development of evidence-based housing policies and practices that prioritise well-being and enhance the quality of housing for individuals and communities.

CRediT authorship contribution statement

Jinfeng Lou: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Bolun Wang:** Writing – original draft, Visualization, Software, Data curation. **Ziqing Yuan:** Software, Methodology, Formal analysis. **Weisheng Lu:** Writing – review & editing, Supervision, Resources, Funding acquisition.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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