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Towards a human-centric city emergency response: Modelling activity patterns of urban population

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ABSTRACT

Human-centric management is emerging as a new trend in urban emergency response, which develops management and resource allocation strategies based on activity patterns of urban population and their derived demands. This study aims to construct an MDCEV-based model to capture the activity patternss of different types of residents during urban emergencies. Using a case study in Shanghai, China, the study calibrates and validates the model using resident survey data. In addition, we conducted scenario analyses to explore the impact of promoting community service participation, remote work experiences, and various working patterns on residents' activity patterns. The research discusses the heterogeneity of time allocation patterns among different resident types in urban emergency management contexts and highlights the influence of external interventions on resident activities. Our findings contribute to the development of supporting measures for vulnerable residents and human-centric city emergency response strategies.

1. Introduction

Cities, functioning as a dynamic and complex system where millions of lives intersect, face heightened vulnerability due to their high population density during emergencies. Threats such as resource scarcity, natural disasters, pandemics, and geopolitical tensions threaten urban functionality (Wang et al., 2023a; Zhang et al., 2024; Zhao et al., 2023; Zhou et al., 2024). For example, a recent case is the global transmission of the SARS-CoV-2 virus that causes COVID-19 (Costa et al., 2022). The pandemic not only threatens the health of urban residents but also significantly impacts mobility within cities. The extensive social distancing measures have disrupted physical industries and supply chains, posing economic recession risks in various regions (Wilkinson et al., 2020). Although the immediate impact of COVID-19 is diminishing, its implications have emphasised the importance of adaptive urban governance. Historical events, such as MERS-CoV, the H5N1 influenza virus and other urban disasters, demonstrate the ongoing need for emergency response strategies that can effectively address potential public crises. These events serve as critical reminders of the need to incorporate resilience into urban planning to mitigate the impacts of future emergencies effectively.

Effectively responding to urban emergencies presents numerous challenges (Henkey, 2018). Within diverse and dense populations in urban areas, both natural hazards and human-included emergencies can rapidly disrupt the lifestyles of residents (Cimellaro, 2016; Henkey, 2018). Emergency response strategies should swiftly mitigate losses and protect urban populations and environments as well as accommodate dynamic lifestyles and varied demands. Especially, different resident groups may exhibit significant heterogeneity in experiences of and demands during urban hazards (Counted et al., 2022). For example, vulnerable groups, such as the elderly, immigrants, ethnic minorities, low-income populations, and marginalised community residents, may face more severe impacts during emergencies or experience stronger fluctuations in lifestyles (Simon et al., 2021; Yin et al., 2021). Also, restricted urban mobility could expose small business owners to increased income risks (Wilkinson et al., 2020).

Urban emergency management necessitates the scientific allocation of limited resources, accurate information management within complex social networks, and the protection of public health amidst evolving activity patterns. Overlooking individual differences and activity pattern fluctuations can compromise meeting the demands of specific resident groups, potentially impacting the effectiveness of emergency

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response (Richard Eiser et al., 2012). Human-centric emergency response emerges as a promising strategy for managing the increasing complexity of urban disasters (Dargin and Mostafavi, 2020). This approach prioritises the behaviours and experiences of people in hazards. For example, Dargin and Mostafavi (2020) explored individual variations in well-being risks resulting from infrastructure disruptions during disasters, aiding urban resilience planning. Wang et al. (2023a) revealed subjective well-being changes among vulnerable resident groups during urban emergencies, emphasising community resilience building to mitigate quality-of-life declines in marginalised communities. Park et al. (2022) proposed response improvements based on analysing travel behaviour changes around transportation hubs during the COVID-19 context. Yoon et al. (2024) simulated the differences in resident behaviours during the pandemic to enhance indoor safety management. These studies highlight the critical need for tailored emergency management strategies that address specific resident needs and behavioural patterns. By integrating insights into individual and group differences, emergency management practices can be refined to improve effectiveness, and ensure equitable resource distribution.

Many human-centric studies found that activity patterns of urban populations play a crucial role in assessing the spatiotemporal distribution of resource and service demands. These patterns including activity types, timing, duration, and location choices, often undergo significant fluctuations during crises. For instance, Henson et al. (2009) advocated for activity-based models to consider the changing time-use patterns in instantaneous disaster preparedness and homeland security, an approach that influenced subsequent emergency management cases like the Haifa wildfire (Toledo et al., 2018) and Miami hurricanes (Yin et al., 2014). Recent research has expanded to address persistent disasters such as COVID-19. During this pandemic, widespread implementation of social distancing and city lockdowns accelerated remote work and online education, leading to complex variations in residents' spatial usage patterns, energy demands, and subjective well-being (Batur et al., 2023; Giurge et al., 2020; Wang et al., 2023a). In addition to working pattern changes, some regions also observed changes in sleep patterns (Cellini et al., 2020). These shifts directly impact optimal evacuation routes or shelter plans (Henson et al., 2009; Pel et al., 2012), distribution of resources, information, and service demands (Franch-Pardo et al., 2020), as well as spatial equity and residents' quality of life (Andrew et al., 2020). Collectively, these cases discussed the influence of changes in specific behaviours (e.g., evacuation, social media use) and activity time use (e.g., paid work, sleep) during urban emergencies, emphasising the importance of understanding dynamic activity patterns in urban crisis management.

Urban disasters and emergencies can significantly impact residents' activity patterns, leading to complex and enduring effects. These events can influence residents' travel destinations and choices of transportation modes. The widespread adoption of remote work during the COVID-19 pandemic has further transformed time allocation, such as leisure and entertainment preferences. During the COVID-19 pandemic, research focusing on time use patterns across different population groups has gained significant momentum (Andrew et al., 2020; Bu et al., 2021; Cellini et al., 2020). While the direct impacts of the pandemic have gradually controlled, an in-depth exploration of these activity trends and their implications for emergency management practices holds significance for developing human-centric urban emergency responses and enhancing community resilience. This study develops a multiple discrete-continuous extreme value (MDCEV)-based model to explore how different urban populations allocate time during urban emergency management, employing Shanghai, China as a case study. This research then adopts the calibrated and validated model to test a series of scenarios. The resulting findings contribute significantly to our understanding of the activity pattern changes among residents during the city lockdowns. These insights shed new light on urban emergency response practices by identifying vulnerable population groups during various urban emergencies. Also, the study contributes to proposing urban-scale digital twins for inclusive and human-centric strategies for resource allocation and information management (Ding et al., 2023; Wang et al., 2025; Ding et al., 2024).

The remainder of this paper is structured as follows: Section 2 introduces the data and model employed in the study. Section 3 presents model calibration and validation. Section 4 conducts scenario setting and analyses. The next section discusses the policy implications based on the results and also reflects the limitations and future research directions. The study is then concluded in Section 6.

2. Data and methods

2.1. Study area and data collection

Shanghai, one of the most densely populated and economically developed regions in mainland China, faced a severe SARS-CoV-2 virus outbreak starting in March 2022 (Burki, 2022; Zhang et al., 2022). During this period, over 600,000 residents were infected within a short span. While the containment measures effectively curtailed virus spread (Chen et al., 2022; Zhang et al., 2022), they also impacted local supply chains, strained healthcare resources, and affected the economy (Zhou et al., 2022, 2023).

The study employs survey data collected from Shanghai residents during the city-emergency period. The survey initially collected personal and household characteristics of the residents including sociodemographic information such as age, gender, household income, and employment status, including the industry primarily work in, and experience with remote work. The survey then recorded the residence environment, covering primarily living location, subjective evaluation of living space, and community conditions. The survey next recorded the subjective assessment of the quality of life during the lockdown, including aspects such as food quality and quantity, medical services, information acquisition, and neighbourhood relations. Another essential part of the survey was the time use dairy, designed with reference to the Harmonised European Time Use Surveys (HETUS) and the 2017 China Household Finance Survey (Survey and Research Center for China Household Finance, 2017). This section recorded respondents' main activities and locations at 30-min intervals over 24 h, from 5:00 a.m. to 4:30 a.m. the next day.

The researchers conducted an online survey via mainstream local online platforms between April and May 2022. This approach held significant advantages for data collection during the city lockdown. Online surveys offered flexibility, allowing respondents to participate without the constraints of traditional face-to-face data collection as well as its derived health risks. The feasibility of this method was enhanced by Shanghai's demographics: the above-average economic status and education levels of the city contributed to a significantly higher internet penetration rate among its residents compared to the national average, laying a solid foundation for online data collection in the city (Wang et al., 2023a,b).

Before the large-scale questionnaire distribution, a small-scale pilot study was conducted. Based on respondent feedback and suggestions, the questionnaire has been refined to improve clarity and reduce ambiguity. The survey respondents meet the following criteria: (1) Current Shanghai residents who have been living in the city as their main residence for at least three months, (2) Individuals with full working capability, (3) Those who do not work night shifts. The survey received a total of 459 valid questionnaires. Table 1 presents the demographic profiles of these respondents.

Table 1 provides a demographic profile of the survey respondents. This profile largely aligns with Shanghai's population characteristics, with the exception of gender distribution, where there is a higher proportion of female respondents compared to males. Hukou, an official document issued by the Chinese government, certifies legal residency in a particular area and often confers priority access to healthcare, education, social welfare, and housing (Afridi et al., 2015; Qian et al., 2020).

Table 1
Demographic characteristics of respondents.

Item and Category	Frequency (n)	Percentage (%)
Age		
Less than 30 yrs	234	50.98%
30–60 yrs	217	47.28%
No less than 60 yrs	9	1.96%
Gender		
Male	201	43.79%
Female	258	56.21%
Local (Shanghai) hukou		
Hold	299	65.14%
Do not hold	160	34.86%
Housing ownership		
Hold	311	67.76%
Do not hold	148	32.24%
Household income (CNY per year)		
Less than 50k	64	13.94%
50k to 100k	58	12.64%
100k to 200k	129	28.10%
200k to 300k	83	18.08%
300k to 500 k	79	17.21%
No less than 500k	46	10.02%
Residential area		
Less than 50 sqm	101	22.00%
50 to 100 sqm	188	40.96%
No less than 100 sqm	170	37.04%
Residential location		
Central districts	185	40.31%
Sub-central districts	274	59.69%
Duration of social media exposure		
No more than 30 min	6	1.31%
0.5–2 h	129	28.10%
2–4 h	245	53.38%
Over 4 h	80	17.43%
Community health services supply evaluation		
Sufficient	208	45.32%
Less sufficient	251	54.68%
Community services participation		
Yes	261	56.86%
No	198	43.14%
Remote working experience		
Yes	370	80.61%
No	89	19.39%

Of Shanghai's 24.197 million residents, 14.5 million have local hukou, reflecting the city's large immigrant population. Approximately 65% of respondents hold local hukou in Shanghai, aligning with the city's overall population distribution. The study defines Shanghai's central urban area as comprising seven districts: Huangpu, Xuhui, Changning, Jing'an, Putuo, Hongkou, and Yangpu. Other administrative districts are classified as non-central areas. In the samples, 40.31% of respondents lived in the central urban area while 59.69% resided in non-central areas. Respondents reported an average social media exposure time of 3.47 h, consistent with data from a large-scale survey conducted during China's city lockdowns (21.4 h per week) (Luo, Chen and Liao, 2021). In addition, about 45.32% of respondents expressed satisfaction with health services during the lockdown. Furthermore, 56.86% of the respondents participated in community volunteer services during the outbreak of the SARS-CoV-2 virus, including supporting nucleic acid testing, logistics, taking care of vulnerable neighbours (e.g., seniors, children, pets etc.), mental health supporting, security and other community services. A majority of respondents (80.61%) had work-from-home experience before the pandemic and city lockdown.

2.2. Data processing

This study categorised residents' activities into eight types. (1) Paid work, including work-related paid tasks. (2) Unpaid work, including voluntary unpaid community services, unpaid tasks attached to work (e.g., the compulsory party history and political studies), and other non-work-related duties (e.g., the compulsory nucleic acid testing) (3) Domestic work, including at-home housework (e.g., laundry and cooking). and out-of-home household tasks (e.g., grocery shopping). (4) Online leisure, such as using social media software and APPs, online news browsing, playing online games, etc. (5) Offline leisure, including both indoor offline and outdoor entertainment activities. (6) Personal care, refers to essential tasks that individuals need to perform daily to maintain their well-being and overall health (excluding sleep), such as eating and showering. (7) Sleep, and (8) Transport. The study also categorised the activity timing into (1) traditional working hours (08:30 to 18:30), and (2) others (18:30 to 8:30). Similarly, considering the restricted urban mobility and transport services under the emergency, the choice of activity location was simplified into two categories: (1) at home and (2) out of home.

Fig. 1 illustrates the distribution of residents' time during the period when Shanghai was under attack from the pandemic. Table 2 further compares the total time allocation patterns of residents during the city-wide emergency with the data from the Shanghai Metropolitan Area Resident Time-use Survey (SMARTS), collected locally after the lifting of the lockdown in autumn 2022. During the pandemic, respondents spent an average of 285.16 min (4.75 h) on paid work and 140.33 min (2.34 h) on unpaid work. The total work time for residents was 425.49 min (7.09 h), compared to 507.04 min (8.45 h) post-lockdown. Moreover, although residents spent more time at home during the pandemic, the time they spent on domestic work (117.32 min, 1.95 h) and personal care (101.11 min, 1.69 h) was significantly less compared to after the city's intervention measures ended (136.64 min and 149.06 min, respectively). Conversely, residents spent 254.64 min (4.24 h) on leisure and entertainment activities (such as browsing social media and watching TV), which is 3.63 times the amount of time spent on these activities after the end of the pandemic.

Fig. 2 illustrates the activity location choices of residents. During the pandemic, the average at-home time for residents (1309.54 min) is significantly higher than the out-of-home time (130.46 min). Out-of-home activities primarily took place between 6:30 and 21:00, peaking at around 9:00 in the morning. Approximately 20% of residents (n = 89) engaged in activities outside their homes. Fig. 3 details the type of out-of-home activities chosen by residents. Between 8:00 and 18:00, residents in out-of-home environments were mainly engaged in paid and unpaid work-related activities. The proportion of these activities gradually declined after 18:00. Since some communities allowed residents to participate in outdoor activities such as physical exercise and dog-walking within gated areas while maintaining social distancing, a group of residents (n = 40, 8.71%) was able to engage in outdoor leisure and recreational activities between 18:00 and 20:00.

2.3. Modelling methods

2.3.1. Working pattern identification

Due to strict urban mobility restrictions, this study focuses on the temporal dimension of work patterns rather than the spatial dimension. Activities were categorised into two states: work and non-work, based on their time allocation. The study employed the k-means clustering method to identify distinct work patterns among residents during the pandemic period. K-means clustering is a technique in data science for partitioning datasets into distinct, meaningful groups or clusters. This technique has facilitated widespread application across multiple interdisciplinary domains, including urban studies (Kimpton, 2017; Zhan et al., 2024) and disaster management research (Sun et al., 2022). The study employs the paid work time choice of the respondents (i.e., if they are performing paid work activity at each time point) as data input. The number of clusters was determined using the Euclidean distance method, followed by K-means clustering analysis, and subsequently validated using ANOVA.

2.3.2. Activity pattern modelling

To capture the time-use patterns of urban populations during urban

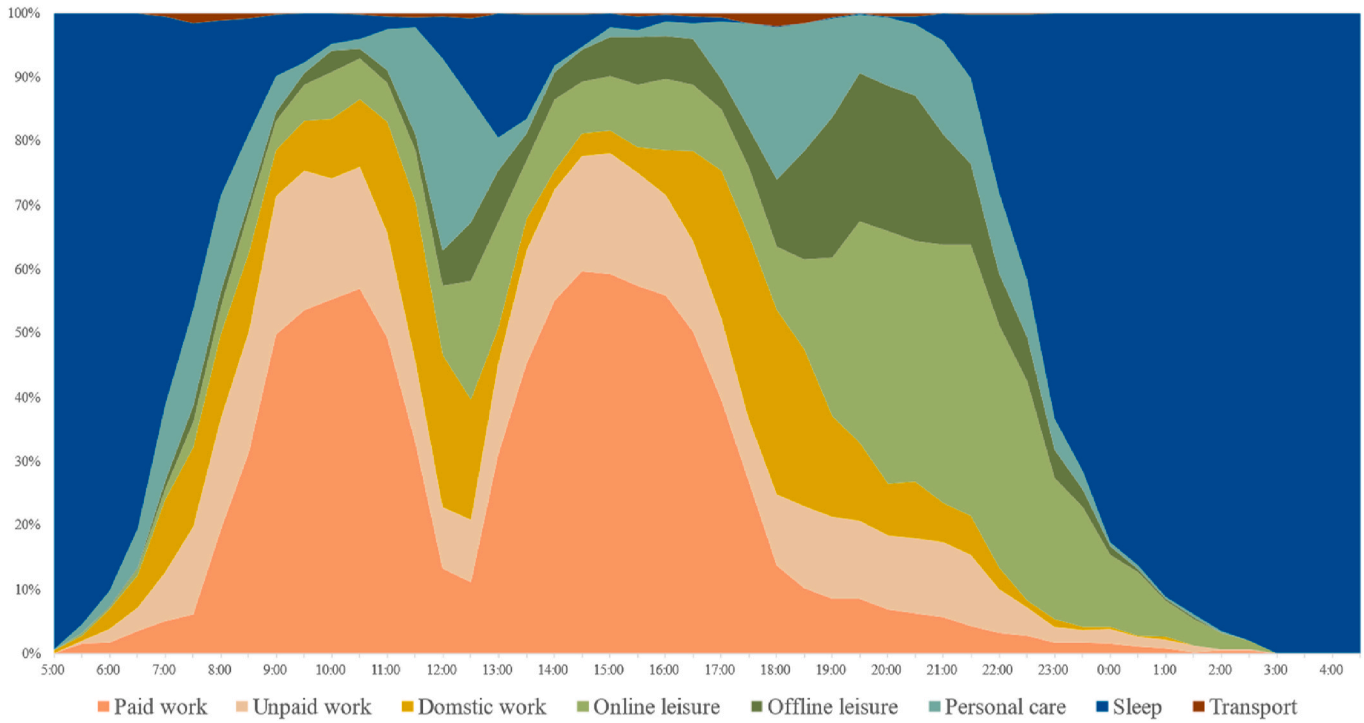

Fig. 1. Overall time use allocation by activity type.

Table 2
Overall time allocation during and after the pandemic.

Activity Category	Pandemic (unit: min)	Post-Pandemic (unit: min)
Work [a]	425.49	507.04
Domestic work	117.32	137.64
Leisure [b]	254.64	70.11
Personal care	101.11	149.06
Sleep	536.54	511.23
Transport	4.90	64.93

Notes.
[a] The item *Work* includes both paid and unpaid work-related activities.
[b] The item *Leisure* includes all online and offline activities related to leisure, entertainment, and hobbies.

emergencies, this study employs the Multiple Discrete-Continuous Extreme Value (MDCEV) model based on utility maximisation theory. Bhat (2005) first introduced the MDCEV model, relaxing the mutual exclusivity assumption inherent in traditional discrete choice models. This model allows decision-makers to allocate budgetary resources across multiple distinct choice combinations, rather than being confined to a single option (Bhat, 2005, 2008; Bhat et al., 2016). Over the subsequent decade, the MDCEV series of models has rapidly evolved (Astroza et al., 2018; Bhat, 2015; Bhat et al., 2016, 2022; Mondal and Bhat, 2021) and found widespread application in various domains, including transportation (Palma et al., 2023; Saxena et al., 2022; Tapia et al., 2020), energy management (Iraganaboina and Eluru, 2021), and consumer behaviour (Park et al., 2023). For activity pattern modelling, this study employs randomly sampled 66.67% of data for model calibration and the other 33.3% for validation.

The MDCEV model employs a direct utility function (see Equation (1)). In this model, different agents allocate non-negative time interval vectors (denoted as $\boldsymbol{x}$) to $\boldsymbol{K}$ activities with distinct characteristics, aiming to maximize their utility. Within the vector $\boldsymbol{x}$ consideration is given to an outside good, that is an essential activity for all agents (with time allocation greater than zero). The time allocation of residents is subject to their time budget constraint, ensuring that the sum of different activity types conducted by an agent throughout the day equals 1440 min. The study assumes that there is no price variation among the activities. Following Bhat (2018), the direct utility formula (a gamma-profile) used in this study is as follows:

$$\text{Maximise } U(\boldsymbol{x}) = \varphi_1 \boldsymbol{x}_1 + \sum\nolimits_{k=2}^{K} \gamma_k \varphi_k \ln\left(\frac{\boldsymbol{x}_k}{\gamma_k} + 1\right) \tag{1}$$

Subject to $\sum\nolimits_{k=1}^{K} \boldsymbol{x}_k = T$ ($T = 1440$ *minutes*)

Where $U(\boldsymbol{x})$ represents the overall utility of time allocation choice $\boldsymbol{x}$, which is a quasi-concave and continuously differentiable function. $\boldsymbol{x}$ is a vector of dimension $(\boldsymbol{K} \times 1)$ reflecting the time allocation to activity type $\boldsymbol{x}_k$, where $\boldsymbol{x}_1 > 0$ for the outside good (i.e., k = 1 for sleep in this study) and $\boldsymbol{x}_k \geq 0$ for other inside goods (i.e., $k \geq 2$). Both the parameters γ_k and φ_k are associated with activity k. γ_k Introduces the corner solutions for inside goods, making it possible for cases where no time is allocated to some activities. There is no γ_1 for the outside activity (sleep) as its compulsory for all residents. Also, γ_k plays the role of a satiation parameter, controlling the satiation effects of the activity k's utility for the agents. Lower values of γ_k refers to a higher satiation effect. φ_k is the baseline utility parameter, which is usually parameterised in the form of Function (2):

$$\varphi_1 = \exp(\varepsilon_1) \tag{2}$$

$$\varphi_k = \exp\left(\beta' z_k + \varepsilon_k\right), \text{ where } k \geq 2$$

Where z_k is a set of attributes reflecting the characteristics of agents and their preference at the specific choice environment for activity types k, β' is the corresponding coefficients associated with these attributes and ε_k refers to the unobserved idiosyncratic effects.

The study considers the impact of several variables on baseline utility during the COVID-19 city lockdown. These variables are summarised in Table 3. Among the considered factors, only social media time and family income are continuous variables, the rest are categorical.

The study assumes that the ε_k items are independent and distributed with a Type-I extreme value and the scale parameter is σ. For the probability that individuals allocate their time into the first M

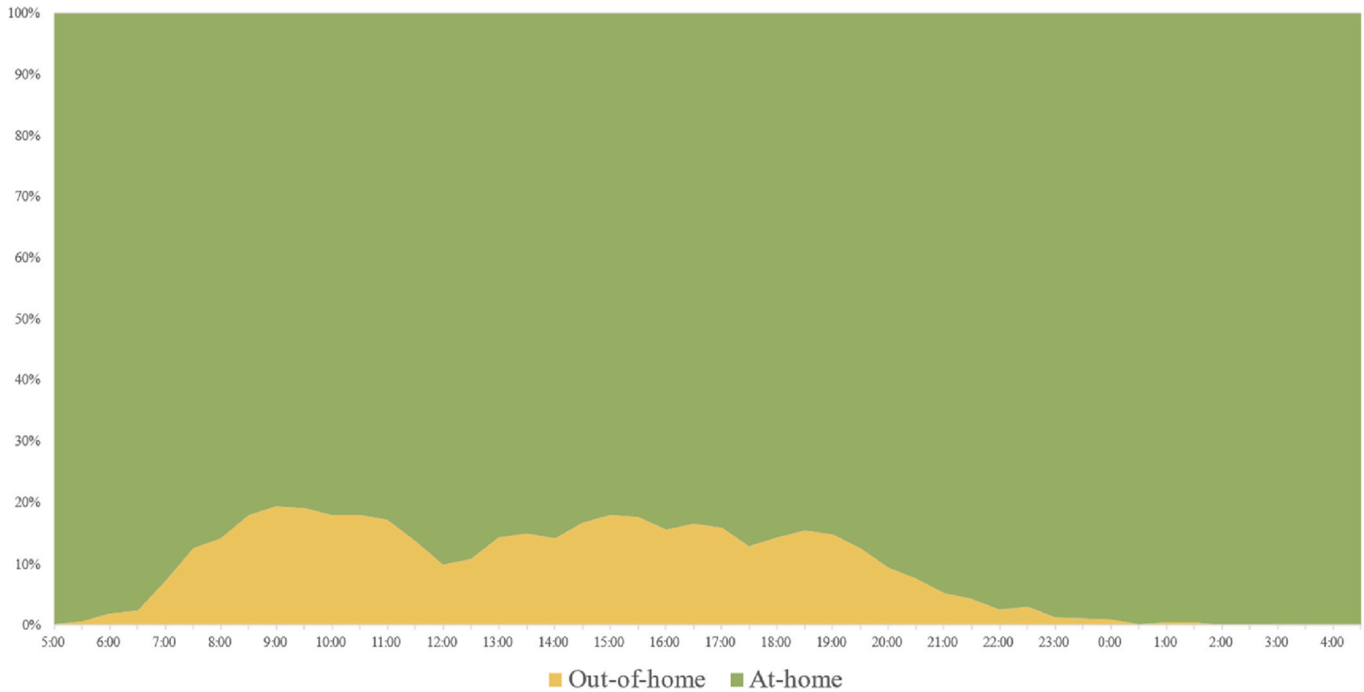

Fig. 2. Overall activity location choice pattern.

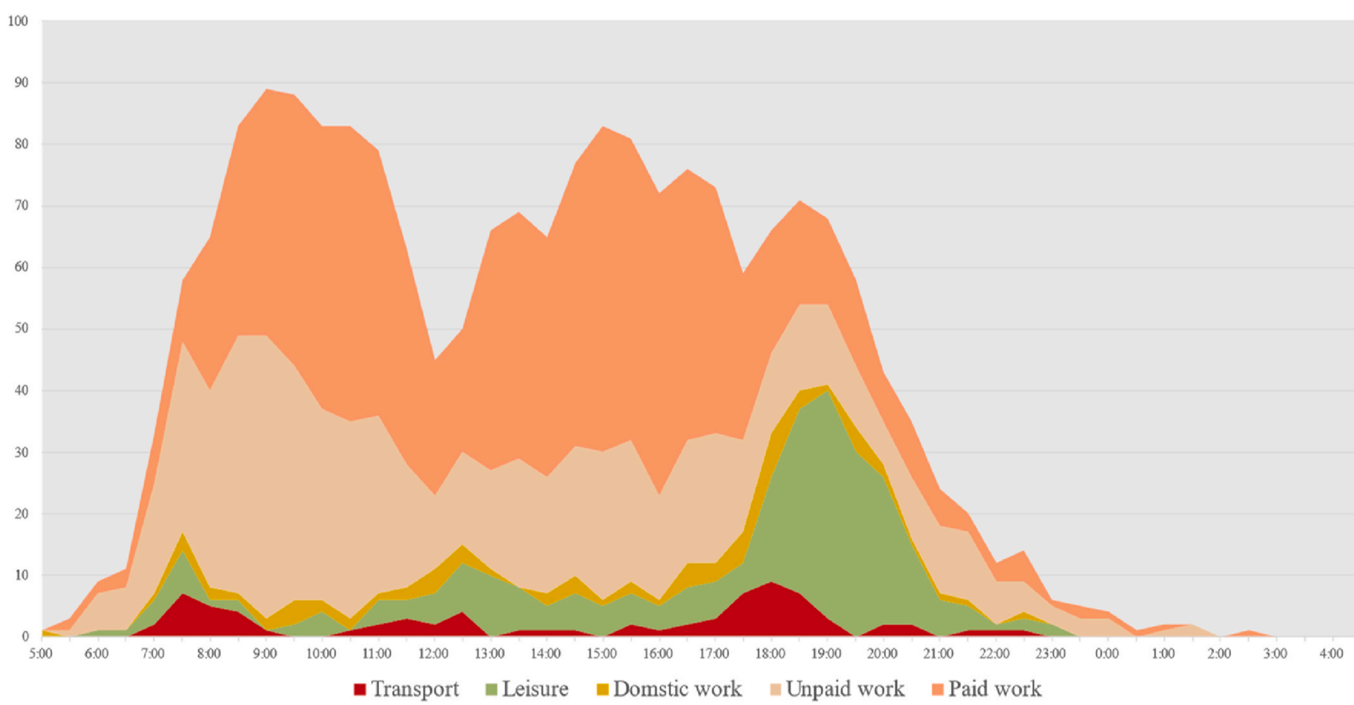

Fig. 3. Overall outdoor activity choice frequency.

Table 3
Explanatory factors used in the model.

Variable	Type of variable	Description	Unit
Social media time	Continuous	Mean = 3.469 Range: 0 to 12	hour
Family income	Continuous	Mean = 249.59 Range = 15 to 1010	1000 CNY *(1 USD≈7.25 CNY)*
Community service role(s)	Categorical	1 = hold 2 = not hold	N/A
Gender	Categorical	1 = female 2 = male	N/A
Hukou	Categorical	1 = nonlocal hukou 2 = local hukou	N/A
Health service satisfaction	Categorical	1 = negative 2 = positive	N/A
Remote working experience	Categorical	1 = no 2 = yes	N/A

$(1 < M \leq K)$ activities among K alternatives (i.e., $x = x_1^*, x_2^*, x_3^*, \ldots, x_M^*, 0, \ldots, 0)$ can be illustrated in Function (3):

$$P\left(x_1^*, x_2^*, x_3^*, \ldots, x_M^*, 0, \ldots, 0\right) = \left[\prod_{i=1}^{M} c_i\right]\left[\sum_{i=1}^{M} c_i\right]\left(\frac{\prod_{i=1}^{M} e^{V_i}}{\left(\sum_{k=1}^{K} e^{V_k}\right)^M}\right) \times (M-1)! \tag{3}$$

Where c_i can be presented by $c_1 = \left(x_1^*\right)^{-1}$ (for $i = 1$) and $c_i = \left(x_i^* + r_i\right)^{-1}$ (for $i \geq 2$). Also, V_i can be given by $V_1 = -\ln\left(x_1^*\right)$ (for $i = 1$) and $V_i = \beta' z_i - \ln\left[x_i^*(\gamma_i)^{-1} + 1\right]$ (for $i \geq 2$).

3. Modelling results

3.1. Clustering the working patterns

The study employed k-means analysis to identify the working patterns of the urban population. Two clusters were determined for residents' work patterns using the Squared Euclidean distance and Ward's linkage method. Subsequently, k-means classification was performed with the tool SPSS Statistics 23.0. The first cluster comprised 271 individuals, while the second cluster included 188 samples. An ANOVA test conducted on the classification results revealed significant heterogeneity in daytime work time choices among the resident categories. The ANOVA results are presented in Appendix I.

Fig. 4 compares the time allocation of the two working pattern groups. The first working pattern group, covering 271 respondents, is referred to as daytime workers. Their work-related activities primarily occur during traditional working hours, totalling 492.95 min (8.22 h) throughout the day. Between 12:00 and 13:30, these residents allocated time to domestic work (e.g., cooking), personal care (e.g., having lunch), and daytime sleep. Due to restrictions on restaurant operations and food delivery services during urban emergencies, residents were more likely to spend time cooking. Non-work-related domestic work and leisure activities were mainly concentrated in the evening. On average, this group of residents spent 106.38 min (1.77 h) on domestic work and 208.45 min (3.47 h) on leisure activities throughout the day.

The second working pattern cluster, consisting of 188 members, has been named flexible workers. They spent 328.24 min (5.47 h) on work-

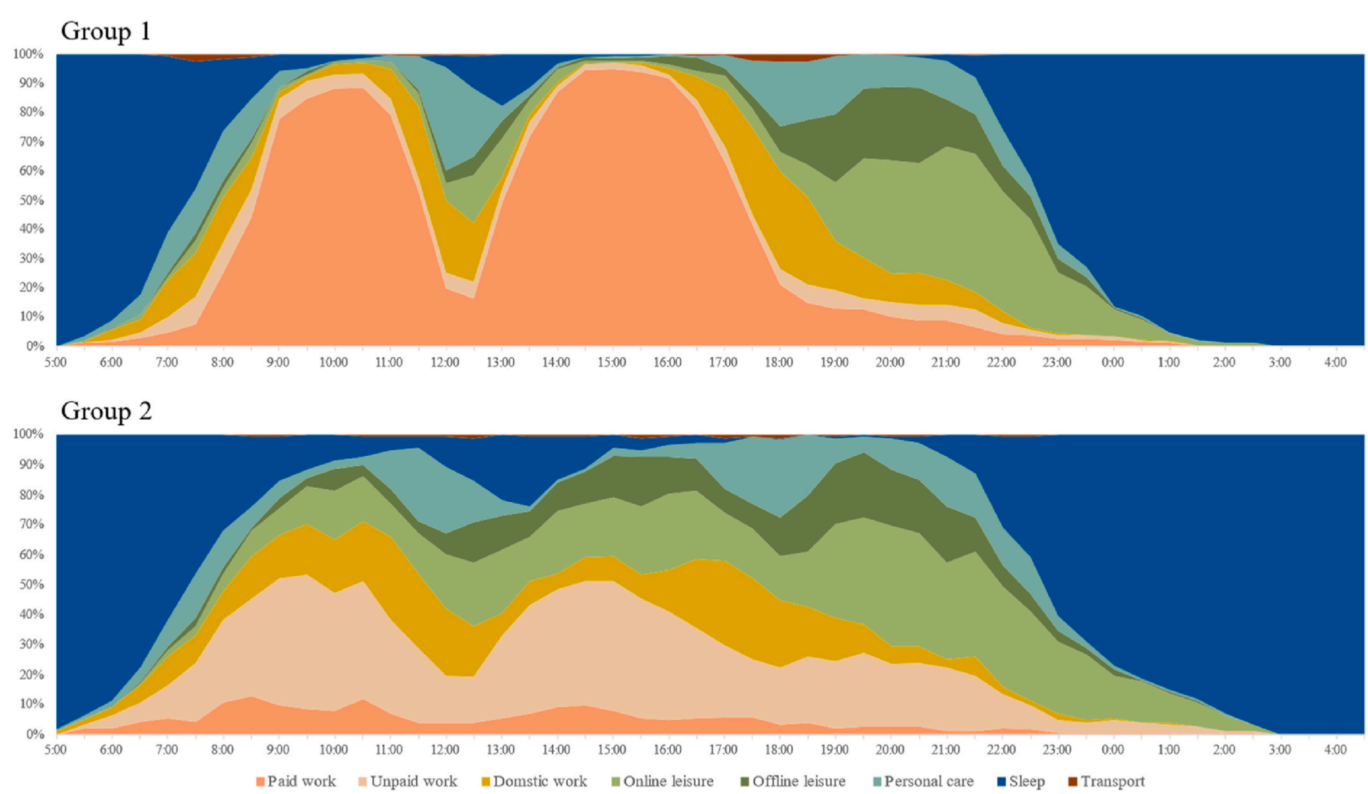

Fig. 4. Time allocation characteristics of two working patterns.

Table 4
Estimated baseline utility and translation parameters.

Time		Daytime working hours (8:30–18:30)				Non-daytime hours (18:30–8:30)			
Parameter		Baseline utility parameter (ψ)		Translation parameters (γ)		Baseline utility parameter (ψ)		Translation parameters (γ)	
Location	Activity	Coeff.	*t-ratio*	Coeff.	*t-ratio*	Coeff.	*t-ratio*	Coeff.	*t-ratio*
At-home	Work (Paid)	−5.20	−16.65	101.78	6.73	−6.60	−15.40	53.79	5.46
	Work (Unpaid)	−7.98	−20.40	98.35	6.04	−7.80	−19.10	67.09	6.08
	Domestic work	−5.37	−18.75	32.36	8.66	−5.96	−19.70	28.04	8.69
	Leisure (Online)	−7.14	−22.36	37.37	7.98	−5.64	−20.37	43.04	8.61
	Leisure (Offline)	−7.18	−19.43	37.73	6.82	−6.08	−20.07	35.84	8.27
	Personal care	−6.29	−21.19	30.45	9.03	−6.02	−20.57	24.66	8.88
	Sleep*	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Out-of-home	Work (Paid)	−6.20	−13.47	104.38	4.43	−7.06	−11.96	55.05	3.59
	Work (Unpaid)	−7.55	−19.62	39.33	6.66	−7.93	−14.87	44.08	4.61
	Domestic work	−7.57	−11.18	32.15	3.40	−8.67	−9.56	29.96	2.51
	Leisure	−8.29	−13.98	35.29	4.19	−7.05	−16.52	36.07	5.76
	Transport	−6.96	−8.26	33.72	2.74	−7.30	−8.57	33.28	2.66

Table 5
Estimated parameters considered in baseline utility functions.

Dimension		Service role (s)	Gender	Hukou	Remote work (before)	Daytime work	Health service	Social media time	Family income
Remark		Not hold	Female	No	No	No	Negative	Unit: min	Unit: CNY
Location	Activity	Time: Daytime working hours (08:30–18:30)							
At-home	Work (Paid)	–	0.314 (*1.610*)	−0.363 (*-1.662*)	−1.191 (*-3.490*)	−2.248 (*-8.910*)	–	–	–
	Work (Unpaid)	–	–	–	–	1.857 (*6.845*)	–	0.086 (*1.687*)	–
	Domestic work	–	–	−0.441 (*-2.201*)	–	0.382 (*1.961*)	–	−0.081 (*-1.919*)	–
	Leisure (Online)	–	0.331 (*1.658*)	–	–	1.134 (*5.481*)	0.32 (*1.618*)	–	–
	Leisure (Offline)	–	–	−0.384 (*-1.501*)	–	1.297 (*5.201*)	–	–	–
	Personal care	–	–	–	–	–	–	–	–
Out-of-home	Work (Paid)	−1.134 (*-3.459*)	–	–	1.286 (*3.475*)	−1.794 (*-4.784*)	–	–	−0.002 (*-2.632*)
	Work (Unpaid)	−0.807 (*-3.278*)	–	–	0.459 (*1.599*)	0.976 (3.876)	–	–	–
	Domestic work	−0.886 (*-1.801*)	−0.931 (*-2.032*)	–	–	1.051 (*2.146*)	−0.757 (*-1.716*)	−0.253 (*-1.883*)	–
	Leisure		−0.577 (*-1.605*)	–	–	1.161 (*3.007*)	–	−0.181 (*-1.777*)	–
	Transport	−1.292 (*-1.958*)	–	–	–	−0.999 (*-1.655*)	–	–	−0.004 (*-1.854*)
Location	**Activity**	**Non-daytime hours (18:30–08:30 next day)**							
At-home	Work (Paid)	–	–	–	–	−0.915 (*-2.967*)	–	−0.112 (*-1.566*)	–
	Work (Unpaid)	–	–	–	–	1.165 (*4.368*)	–	–	–
	Domestic work	–	–	–	–	−0.496 (*-2.374*)	–	–	–
	Leisure (Online)	–	–	–	–	–	–	–	–
	Leisure (Offline)	–	–	–	–	–	–	–	–
	Personal care	–	–	–	–	–	–	–	0.001 (*1.827*)
Out-of-home	Work (Paid)	−1.048 (*-2.399*)	–	–	1.207 (*2.599*)	−1.453 (*-3.073*)	−1.008 (*-2.554*)	0.161 (*2.013*)	−0.003 (*-2.259*)
	Work (Unpaid)	−0.511 (*-1.586*)	−0.729 (*-2.241*)	–	0.826 (*2.372*)	0.668 (*1.973*)	–	–	–
	Domestic work	–	–	–	–	–	–	–	–
	Leisure	–	−0.662 (*-2.432*)	–	–	–	–	–	–
	Transport	−1.137 (*-1.710*)	–	–	–	−1.348 (*-1.918*)	–	–	–

related activities daily on average. Compared to the first group, these residents allocated more time to unpaid work activities. Besides traditional daytime work hours, they also engaged in work-related activities in the evening. Additionally, their leisure activity time (133.09 min) exhibited a more dispersed pattern, maintaining relatively stable proportions from morning to night rather than concentrating solely in the evening.

3.2. Estimations of activity pattern model

This study constructed an activity pattern model based on MDCEV (Mixed Data Choice Estimation with Variance) and employed a randomly selected 66.7% sample (N = 306) for model calibration. The calibration process employed Apollo, a widely used modelling tool for discrete choice models, built upon the work of Train (2009) and Hess and Daly (2014). To assess the model's goodness of fit, this study evaluated the Log-Likelihood (LL), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Both the AIC and BIC values for the final model were lower than those of the constant model, indicating an improvement in goodness-of-fit.

Table 4 summarises the estimated baseline utility (ψ) and translation parameters (γ). Baseline utility reflects relative preferences for participating in different activity types during specific time periods. Calculations often use an external activity, such as sleep, as a reference point because sleep has the highest probability of being chosen as a necessary activity for individuals. Consequently, baseline utility parameters are typically negative. Larger baseline utility parameters indicate greater popularity for a specific activity, meaning residents are more likely to choose it during that time period. For instance, the data reveals that the baseline utility for paid work during the daytime (at-home ψ = -5.20, and out-of-home ψ = -6.20) was higher than that for unpaid work-related activities (at-home ψ = -7.98, and out-of-home ψ = -7.55), which reflects the fact that the aggregated time allocated to paid work is higher than the unpaid work. Also, the analysis supports that the average working hours during non-daytime periods are lower than those observed during daytime hours. Similarly, Shanghai residents exhibit higher average domestic work engagement during non-daytime periods compared to daytime intervals.

The translation parameters (γ) in Table 4 have no direct interpretative explanation, they play an important role in accommodating corner effects and satiation effects. They allow some residents to avoid specific activities (i.e., allocate zero time) and enable activity utilities to vary with time duration. Lower translation parameter values correspond to higher satiation levels within specific activity time categories. The satiation effect is related to how utility decreases as time allocation increases. Slower decreases in satiation allow specific activities to receive longer time allocations when chosen.

Table 5 presents estimated parameters considered in baseline utility functions. Blank cells (indicated by "-") imply that the effect of a certain working pattern on baseline preference is insignificant. Our analysis suggests that community service participation positively impacts the baseline utility for most out-of-home activities. During the COVID-19 pandemic and urban lockdowns, community service participants engaged in outdoor tasks such as centralised nucleic acid testing, video and medical resource transportation, safety security, and sanitation. These activities require residents to venture beyond their home environments.

Another interesting finding is that female residents tend to prefer indoor entertainment over outdoor leisure activities. Regarding workplace choices, women are more likely to work from home and tend to reduce outdoor domestic work (e.g., dog walking, food and resource collection). This finding is also in line with two panel studies in America during the pandemic (Beall et al., 2022; Taff et al., 2021). It suggests that during the pandemic, female residents experienced a more pronounced reduction in outdoor activity time. Beall et al. (2022) critically highlighted that this disruption to outdoor activity patterns could disproportionately impact female residents' subjective well-being and physical health. Shanghai has accommodated a significant population of non-local immigrants, many of whom lack Shanghai household registration (hukou) (Qian et al., 2020). These migrants, often referred to as external/input labour, constitute a major workforce in industries such as logistics, catering, and construction. Data indicates that these residents exhibit less preference for paid work (at home), domestic work (at home), and offline leisure activities (at home). This is in line with another observation in Beijing, China (Lu et al., 2022). This tendency may be due to the nature of their work, which may not support remote work, leading them to engage in outdoor activities during urban emergency management periods. Lu et al. (2022) pointed out that the aforementioned trend of residents without local hukou might face a higher exposure risk of the SARS-CoV-2 virus.

Table 6
Comparison between estimated and observed activity duration.

Time		Daytime working hours (8:30–18:30)		Non-daytime hours (18:30–8:30)	
Location	Activity	Estimated Duration	Observed Duration	Estimated Duration	Observed Duration
At-home	Work (Paid)	165.89	187.45	19.45	14.90
	Work (Unpaid)	57.12	52.35	33.30	30.98
	Domestic work	81.35	72.35	47.33	42.16
	Leisure (Online)	64.68	58.04	125.43	116.67
	Leisure (Offline)	29.51	20.59	45.80	38.04
	Personal care	63.81	48.82	63.64	62.55
Out-of-home	Work (Paid)	30.49	70.20	12.97	10.00
	Work (Unpaid)	28.36	36.08	11.42	14.90
	Domestic work	4.49	3.53	2.41	1.57
	Leisure	7.51	7.84	14.79	9.80
	Transport	2.63	4.71	2.35	2.55

Unit: minute.

3.3. MDCEV validation

This study employed a validation sample comprising randomly selected 33.3% (n = 153) of the total dataset, which was deliberately excluded from model calibration (Cheng and Chen, 2009). This sample proportion is higher than those observed in most model-based research. The rationale for this approach stems from the recognition that the total sample size of this study is small and smaller validation samples of 15% (n = 69) or 20% (n = 91) would potentially compromise the robustness of the validation process, rendering the results more susceptible to the influence of outliers and noise within the dataset. Table 6 presents data from the MDCEV model estimates and observed activity duration for different types and locations. The model results closely reflect real-world time allocation patterns among residents during daytime and non-daytime periods. Fig. 5 displays a scatter plot comparing estimated and observed activity durations for specific time intervals and activity types. For the outside activity, the observed sleep time is 533.92 min, and the estimated sleep time by the proposed model is 530.60 min. To avoid overfitting, our regression model excludes outside activities (i.e., sleep). The coefficient of determination (R-squared) for activity duration is 0.9199 (the R-squared considering the outside activity is 0.9871), indicating the satisfactory predictive performance of the model.

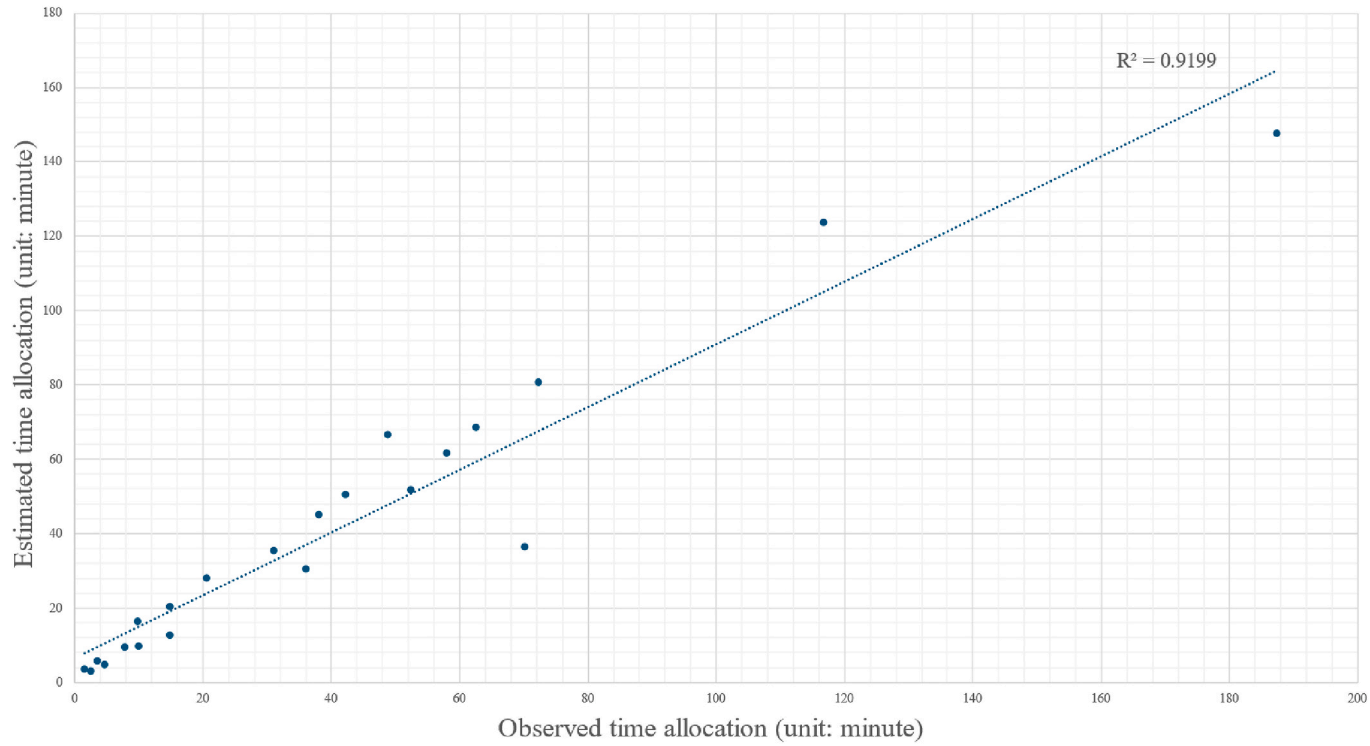

Fig. 5. Validation of the MDCEV model.

Table 7
Scenario setting summary.

Scenario	Intervention(s) and Change(s)		
	Roles in community services	Remote working experience	Working pattern
Baseline	Yes: 261 (56.86%)	Yes: 370 (80.61%)	Daytime: 271 (59.04%)
1(a)	+15%		
1(b)	+10%		
1(c)	−10%		
1(d)	−15%		
2(a)		+15%	
2(b)		+10%	
2(c)		−10%	
2(d)		−15%	
3(a)			+15%
3(b)			+10%
3(c)			−10%
3(d)			−15%
4(a)		+10%	+10%
4(b)		−10%	+10%
4(c)	+10%		+10%
4(d)	−10%		+10%

4. Scenario analysis

4.1. Scenario development

Based on the calibrated model, this study conducted scenario analyses to explore the comprehensive impact of management measures on activity patterns of urban populations in city emergencies. The paper devises 12 scenarios, focusing on three dimensions: (1) Roles in community services. The first group of scenarios (1(a)-1(d)) examines whether residents are allowed to assume managerial or service roles in urban emergency management. These four scenarios vary the proportion of employed residents with roles in community services, with a 15% increase, a 10% increase, a 10% reduction, and a 15% reduction, respectively. (2) Remote working experience. The second group of scenarios (2(a)-2(d)) focuses on whether residents had prior experience with remote work before the emergency. Similar to the first group, these scenarios adjust the percentage of residents with remote working experience, ranging from a 15% increase to a 15% reduction compared to the current baseline. (3) Working Patterns. The third group (3(a)-3(d)) considers residents' working pattern choices during urban emergencies. These scenarios alter the proportion of residents opting for daytime working patterns.

In addition to these three sets of scenarios, this study also proposes four additional scenarios to explore the combined effects of interventions: Scenarios 4(a) and 4(b) primarily consider the joint impact of working patterns and remote working experience. Scenarios 4(c) and 4(d) combine the changes in working patterns and the participation of community services. Table 7 provides a detailed summary of the scenario settings in this study.

4.2. Scenario analysis results

Fig. 6 illustrates the influence of roles in community services, remote working experience, and working patterns on time use changes of four typical activities: out-of-home activities (including both daytime and non-daytime), work-related activities (both paid and unpaid), online leisure time, and sleep duration. Tables 8 and 9 contrast the effects of changes in the three studied dimensions on daytime (8:30 a.m. to 6:30 p.m.) and non-daytime (6:30 p.m. to 8:30 a.m.) time allocation residents, respectively. In addition, the study presents the results of four combined intervention scenarios (4(a) to 4(d)) in Table 10.

The experience of remote working has demonstrated complex implications for the time use patterns of urban populations. During city lockdown periods, rapidly adapting to transformed work modalities while ensuring income security and maintaining subjective well-being and social/community attachment of urban population emerged as critical considerations (Tran et al., 2020; Vieira et al., 2021). Residents with previous remote working experience exhibited greater adaptability

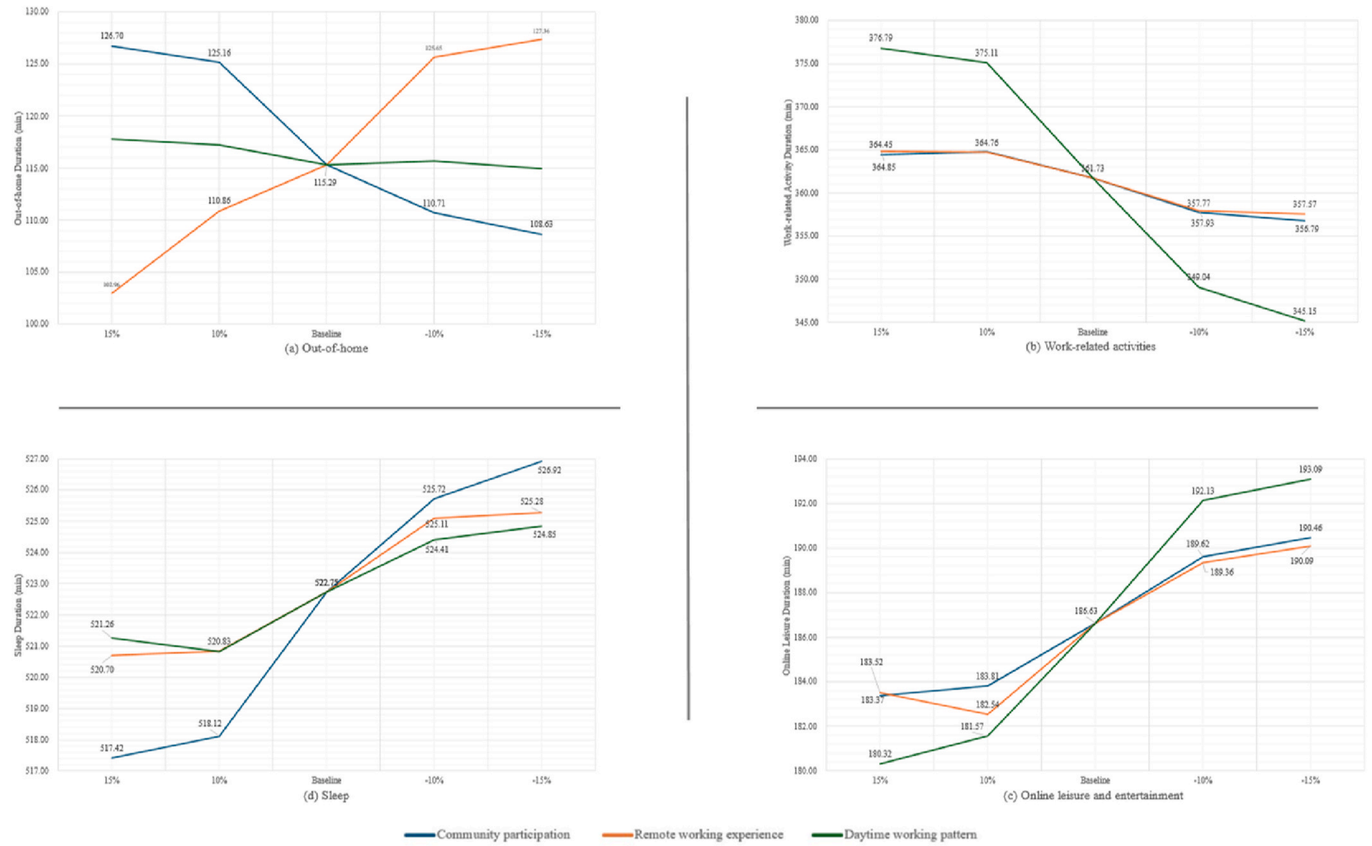

Fig. 6. The changes of four typical activities in the scenario analysis.

Table 8
Daytime Time Use Patterns (Unit: minute).

	Sleep	Work	Unpaid work	Domestic work	Online leisure	Offline leisure	Personal care	Transport
Base	59.7	202.2	83.8	88.6	63.7	37.2	61.9	2.9
1(a)	56.4	200.8	86.6	90.3	62.1	38.8	61.5	3.5
	−5.43%	*−0.71%*	*3.26%*	*1.91%*	*−2.51%*	*4.30%*	*−0.59%*	*21.48%*
1(b)	56.4	201.9	86.1	89.8	62.2	38.7	61.6	3.4
	−5.49%	*−0.16%*	*2.63%*	*1.40%*	*−2.33%*	*3.83%*	*−0.46%*	*17.61%*
1(c)	61.9	201.2	81.9	87.7	64.0	37.7	62.8	2.8
	3.77%	*−0.51%*	*−2.28%*	*−1.03%*	*0.49%*	*1.23%*	*1.48%*	*−2.62%*
1(d)	62.7	201.2	81.3	87.3	64.3	37.6	63.0	2.7
	5.12%	*−0.50%*	*−3.06%*	*−1.45%*	*0.92%*	*0.90%*	*1.76%*	*−6.99%*
2(a)	55.1	209.1	84.2	90.6	60.7	37.4	60.4	2.6
	−7.60%	*3.37%*	*0.37%*	*2.31%*	*−4.79%*	*0.34%*	*−2.36%*	*−9.09%*
2(b)	57.0	206.2	84.8	90.3	59.6	38.6	60.7	2.9
	−4.54%	*1.97%*	*1.13%*	*1.91%*	*−6.44%*	*3.75%*	*−1.94%*	*−0.30%*
2(c)	65.2	195.3	83.9	87.2	65.9	36.6	63.0	3.0
	9.17%	*−3.44%*	*0.03%*	*−1.53%*	*3.47%*	*−1.68%*	*1.77%*	*4.65%*
2(d)	65.9	194.3	83.7	86.7	66.6	36.5	63.3	3.0
	10.45%	*−3.91%*	*−0.23%*	*−2.11%*	*4.60%*	*−1.94%*	*2.25%*	*4.55%*
3(a)	63.5	235.0	68.3	83.8	54.7	31.2	60.3	3.2
	6.45%	*16.22%*	*−18.60%*	*−5.33%*	*−14.21%*	*−16.33%*	*−2.50%*	*12.27%*
3(b)	61.7	229.4	71.5	84.6	56.7	32.5	60.6	3.2
	3.30%	*13.44%*	*−14.69%*	*−4.51%*	*−11.08%*	*−12.79%*	*−2.10%*	*10.32%*
3(c)	58.2	175.9	95.6	92.3	70.8	41.6	63.0	2.6
	−2.41%	*−13.03%*	*14.01%*	*4.20%*	*11.16%*	*11.68%*	*1.79%*	*−8.49%*
3(d)	57.6	167.9	99.4	93.7	72.4	43.2	63.3	2.5
	−3.44%	*−16.96%*	*18.54%*	*5.77%*	*13.57%*	*16.10%*	*2.32%*	*−13.20%*

to work environments under lockdown conditions (Shirmohammadi et al., 2022). As illustrated in Fig. 6, a negative correlation was observed between remote working experience and out-of-home activities. Specifically, when the proportion of residents with remote working experience increased by 15% (Scenario 2(a)), the average time spent on outdoor activities declined by approximately 13 min compared to the baseline scenario. This transformation predominantly originated from the positive impact of remote working experience on daytime work-related activities conducted at home. In Scenario 2(a), residents' average daytime paid-work duration increased from 172.7 min

Table 9
Non-Daytime Time Use Patterns (Unit: minute).

	Sleep	Work	Unpaid work	Domestic work	Online leisure	Offline leisure	Personal care	Transport
Base	463.1	30.7	45.0	49.7	122.9	62.7	63.4	2.6
1(a)	461.0	33.4	43.7	50.2	121.3	62.8	64.6	3.1
	−0.45%	*8.96%*	*−2.93%*	*0.93%*	*−1.35%*	*0.17%*	*1.97%*	*19.24%*
1(b)	461.7	33.1	43.7	50.0	121.6	62.6	64.3	3.0
	−0.29%	*7.95%*	*−2.85%*	*0.60%*	*−1.09%*	*−0.20%*	*1.50%*	*15.27%*
1(c)	463.8	30.6	44.0	49.1	125.6	61.8	62.6	2.5
	0.16%	*−0.15%*	*−2.13%*	*−1.20%*	*2.18%*	*−1.44%*	*−1.22%*	*−5.05%*
1(d)	464.2	30.2	44.1	49.0	126.2	61.6	62.3	2.4
	0.24%	*−1.54%*	*−1.96%*	*−1.46%*	*2.64%*	*−1.67%*	*−1.70%*	*−6.22%*
2(a)	465.5	29.8	41.8	49.2	122.9	64.5	63.6	2.6
	0.54%	*−2.77%*	*−7.02%*	*−1.05%*	*−0.05%*	*2.90%*	*0.37%*	*1.75%*
2(b)	463.9	31.6	42.1	49.3	122.9	63.9	63.6	2.7
	0.17%	*3.01%*	*−6.30%*	*−0.95%*	*0.01%*	*1.95%*	*0.39%*	*4.12%*
2(c)	459.9	32.5	46.3	50.5	123.4	61.1	63.7	2.5
	−0.67%	*5.95%*	*2.91%*	*1.49%*	*0.42%*	*−2.53%*	*0.56%*	*−1.75%*
2(d)	459.4	32.5	47.1	50.7	123.4	60.6	63.8	2.6
	−0.80%	*5.86%*	*4.76%*	*1.86%*	*0.43%*	*−3.31%*	*0.63%*	*−1.09%*
3(a)	457.7	35.1	38.4	52.4	125.7	62.8	64.9	3.0
	−1.15%	*14.49%*	*−14.63%*	*5.33%*	*2.23%*	*0.18%*	*2.47%*	*15.16%*
3(b)	459.2	34.3	39.8	51.7	124.9	62.6	64.5	2.9
	−0.84%	*11.94%*	*−11.40%*	*3.86%*	*1.62%*	*−0.07%*	*1.81%*	*12.87%*
3(c)	466.2	28.7	48.9	47.8	121.3	62.2	62.6	2.3
	0.67%	*−6.45%*	*8.68%*	*−3.94%*	*−1.31%*	*−0.72%*	*−1.15%*	*−10.63%*
3(d)	467.2	27.6	50.2	47.4	120.7	62.1	62.4	2.2
	0.90%	*−9.98%*	*11.67%*	*−4.67%*	*−1.78%*	*−0.88%*	*−1.48%*	*−13.26%*

Table 10
Combined effects of multiple interventions.

Time	Activity	Baseline (minutes)	4(a)	4(b)	4(c)	4(d)
Daytime	Outdoor	73.10	1.61%	13.27%	10.87%	−4.76%
	Sleep	59.68	3.30%	11.94%	−2.62%	6.21%
	Paid Work	202.23	13.44%	9.57%	13.40%	13.75%
	-At-home	172.73	12.77%	4.47%	10.80%	14.54%
	-Out-of-home	29.50	17.32%	39.41%	28.63%	9.10%
	Unpaid work	83.85	−14.69%	−14.14%	−11.43%	−16.85%
	Domestic work	88.56	−4.51%	−5.88%	−2.98%	−5.74%
	Online leisure	63.72	−11.08%	−7.87%	−13.38%	−9.98%
	Offline leisure	37.23	−12.79%	−13.28%	−10.14%	−13.96%
	Personal care	61.86	−2.10%	0.08%	−2.80%	−1.25%
	Transport	2.87	10.32%	17.35%	24.89%	0.96%
Non-daytime	Outdoor	42.15	1.76%	7.64%	4.62%	−2.20%
	Sleep	463.06	−0.84%	−1.44%	−0.96%	−0.50%
	Paid Work	30.68	11.94%	15.78%	15.85%	8.01%
	-At-home	20.31	8.76%	6.59%	13.09%	6.28%
	-Out-of-home	10.37	18.15%	33.80%	21.25%	11.41%
	Unpaid work	44.97	−11.40%	−7.40%	−12.11%	−11.28%
	Domestic work	49.74	3.86%	5.15%	4.68%	2.74%
	Online leisure	122.91	1.62%	2.06%	−0.05%	3.17%
	Offline leisure	62.68	−0.07%	−2.41%	0.35%	−0.95%
	Personal care	63.37	1.81%	1.98%	2.87%	0.22%
	Transport	2.58	12.87%	11.64%	28.18%	4.23%

(baseline) to 185.9 min, representing a 13.2-min increment.

In addition, it is interesting to find that no statistically significant contribution was detected regarding remote working experience and non-daytime paid-work activities. A potential explanation suggests that remote working experience enables residents to better manage work tasks, thereby increasing the likelihood of task completion during traditional working hours. While reduced out-of-home activities potentially minimise external environmental exposure, potentially mitigating infectious disease (e.g., SARS-CoV-2 virus) transmission, this reduction simultaneously presents nuanced implications. Decreased outdoor interaction may compromise residents' engagement with natural environments and limit social interactions with community members, potentially compromising subjective well-being and increasing the risk of psychological isolation (Su et al., 2022; Wang et al., 2023a,b).

There are many recent studies discussing the direct implications of remote working, especially the working pattern shifts during COVID-19, on sleep patterns (e.g., Costa et al., 2022; Dolce et al., 2024; Janc et al., 2024). Yuan et al. (2022) and our study demonstrate that the overall sleep duration of urban population increased. However, numerous studies have reported that the widespread working pattern shifts during urban lockdowns may precipitate alterations in sleep patterns. For instance, Janc et al. (2024) documented that remote working employees might systematically postpone their sleep onset times. This study, however, observes the role of prior remote working experience in these dynamics. Fig. 6(d) reveals a notably marginal impact of remote working experience on the total sleep duration of urban populations. Increasing or decreasing the proportion of residents with remote working experience by 15% (Scenarios 2(a) and 2(d)) resulted in only minimal fluctuations, with average sleep time experiencing approximately a 2-min variation. However, a comparative analysis of data from Tables 7 and 8 unveils a more interesting pattern. The proportion of residents with remote working experience presents a directional influence on sleep time allocation: a positive correlation with non-daytime sleep duration and a negative correlation with daytime sleep activities. In Scenario 2(c), for example, where the proportion of residents with remote working experience was reduced by 10%, daytime sleep duration increased by 5.5 min (+9.17%), while non-daytime sleep duration concurrently decreased by 3.2 min. This finding suggests a potential behavioural adaptation among residents with remote working experience, wherein they show a propensity to redistribute sleep time, shifting daytime sleep periods to nocturnal hours. As remote working experience becomes increasingly prevalent, the cities might witness an emerging trend where residents optimise their sleep patterns by compressing daytime sleep intervals (e.g., traditional midday naps) to facilitate more extended non-daytime/nighttime sleep periods.

In addition to the exploration of remote working experience, our scenario analysis discusses the roles of community service participation and working patterns. First, the analysis suggests that community service engagement demonstrated a significant positive correlation with residents' out-of-home activity time allocation. Fig. 6(a) illustrates an empirical observation: when community service participation increased by 15% (Scenario 1(a)), the average out-of-home activity duration for urban populations expanded by 11.41 min (+9.90%) compared to the baseline scenario. This augmentation of out-of-home activities presents potentially substantial implications for residents' psychological and physical well-being during urban lockdown periods (Su et al., 2022). By increasing outdoor environmental exposure, individuals may mitigate the deleterious psychological influence associated with prolonged isolation. Moreover, enhanced community participation facilitates more robust interpersonal connections, enabling residents to establish relationships with other community members (Wang et al., 2023a). Therefore, such interactions can improve community attachment and social well-being, serving as a social resilience mechanism during pandemic/emergency-induced city constraints.

The scenario analysis, however, also revealed nuanced complexities inherent in community service engagement during urban emergencies. Community service infrastructure might necessitate extended operational hours, potentially extending into late-night periods to support essential services such as daily testing and necessary supply distributions. These operational demands can significantly influence participants' sleep patterns and time allocation. For example, increasing community service participation by 10% (Scenario 1(b)) corresponded with modest but noteworthy reductions in the average sleep and online leisure/entertainment time of urban population, about 5 and 3 min, respectively. Also, this scenario demonstrated a 7.95% increase in non-daytime paid work time allocation among participants. This finding suggests an intriguing adaptive strategy: residents engaged in community services might be more likely to redistribute their paid work activities to non-daytime hours. This time reallocation potentially serves to mitigate the income security implications arising from daytime unpaid community services (Lai et al., 2023).

Among the three dimensions, the working pattern has the most significant impact on residents' work-related activities and online leisure time. As the proportion of daytime working patterns increases, residents' work hours rise rapidly, covering both at-home and out-of-home work-related activities. Conversely, promoting daytime working patterns may reduce indoor leisure time due to a significant decline in daytime leisure activities. With increased daytime working patterns, residents' offline leisure remains relatively stable, while online leisure activities show an upward trend. This reflects the fact that residents adopting daytime working patterns concentrate their leisure needs during non-daytime hours.

The study also observed the variations in sleeping duration and domestic work across different scenarios. Our model analysis demonstrates that both community service participation and remote work experience contributed to a reduction in daytime sleep duration. However, a critical distinction emerged in their impact on non-daytime sleep patterns. Unlike remote work experience, there is no positive connection between community service participation and non-daytime sleep duration. An increase of 15% in community service participation (Scenario 1(a)) resulted in a marginal decrease of 1.9 min (i.e., −0.41%) in non-daytime sleep duration. Despite this nuanced difference, both community service participation and remote work experience shared a common characteristic: a moderate positive effect on daytime domestic work. However, the adoption of daytime working patterns plays a different role: A 15% increase in daytime working pattern proportion (Scenario 3(a)) positively extended the daytime sleep duration of urban population while simultaneously significantly reducing daytime domestic work allocation by 4.8 min compared to the baseline scenario. The analysis suggests that this reduction was accompanied by a compensatory mechanism: Scenario 3(a) witnessed a 5.33% increase in non-daytime domestic work, comprising a 3.67% increase in non-daytime at-home domestic work and a 5.41% increase in non-daytime out-of-home domestic work relative to the baseline. This pattern reflects a deeply ingrained cultural practice in mainland China, where midday rest periods constitute a primary component of daytime sleep time allocation. The scenario analysis suggests that employed residents adopting daytime working patterns may reduce daytime domestic work to preserve midday rest, subsequently redistributing these tasks to non-daytime hours.

Table 10 presents the results of four combined intervention scenarios (4(a) to 4(d)). From the perspective of daytime paid work duration, community service participation appears to have no significant impact on working patterns. However, when delving into the location choice for paid work, community service involvement tends to encourage residents to allocate more daytime paid work to out-of-home environment settings. Engaging in community activities provides residents with increased opportunities for outdoor exposure. While this exposure may carry infection risks, it also mitigates the adverse effects of prolonged home isolation on mental and physical health (Brodeur et al., 2021; Sibley et al., 2020).

Furthermore, community service participation reduces the negative impact of daytime working patterns on unpaid work duration. Although reducing remote working experience leads to increased outdoor working duration during the day, it significantly decreases the time residents allocate to at-home office work, thus negatively affecting overall paid work hours. During urban emergencies, maintaining stable paid work hours directly correlates with income stability, helping alleviate the impact of lockdown measures and associated negative feelings and emotions (e.g., anxiety, loneliness, and stress) (Su et al., 2022). Also, remote working experience enhances the regulatory effect of working patterns on online leisure activities. Leisure activities play critical roles in subjective well-being and quality of life (Brajša-Žganec et al., 2011). Excessive exposure to social media can impact residents' emotions and potentially lead to addiction (Nie et al., 2017; Valkenburg, 2022), which has been widely observed during the city lockdowns (Foa et al., 2020). Remote working experience can better balance people between online and offline entertainment preferences.

5. Implications and future directions

5.1. Implications

The study examines activity patterns among the urban population during the COVID-19 pandemic, using it as a case study. In the post-COVID-19 era, our model contributes to urban emergency management in two significant ways. First, it provides an activity-based analytical framework for capturing the dynamic residential sector demands by examining time-use patterns during urban emergency scenarios. Second, it develops a nuanced approach to designing targeted intervention strategies based on granular resident characteristics, offering a methodological blueprint for adaptive urban management.

Understanding time use patterns of urban population provides valuable insights for urban public management, enabling more effective and people-centred emergency measures (Wang et al., 2023a). Our model framework provides a novel methodology for urban emergency management and strategic planning. By providing an accurate mapping of resident activity patterns, the framework enables decision-makers and service providers to develop more adaptive and anticipatory urban governance strategies across diverse emergency scenarios. The model's core strength lies in its ability to capture the complex, multi-dimensional interactions between urban residents, spatial resources, emergency conditions and interventions. Beyond the pandemic contexts, this approach has the potential to play important roles in various urban emergency scenarios, such as natural disasters, climate-induced disruptions, and potential supply chain crises (e.g., energy and food). The model can capture the activity pattern changes of different resident groups under these different urban emergency scenarios, and support revealing the temporal and spatial characteristics of the space, resources and service demands derived from their activities. This could support policymakers in developing people-centric and data-driven intervention strategies. For example, community managers could develop more customised service delivery schedules considering the working pattern sharing of the residents, to create more inclusive and resilient support systems (Liu et al., 2023). The research underscores the importance of understanding activity adaptations as a critical component of emergency management, moving beyond traditional top-down approaches towards more responsive activity-based urban governance models.

The research also presents the heterogeneous adaptive activity patterns exhibited by diverse population groups during emergencies, revealing insights into the differential vulnerabilities inherent in urban emergency response mechanisms. Our analysis specifically uncovers the disproportionate impacts on vulnerable urban populations, with particularly pronounced effects on some demographic segments, such as females, immigrants (i.e., residents without local hukous), and individuals lacking prior remote working experience. The empirical findings demonstrate that these population groups experience more substantial disruptions in their original lifestyles under city emergency scenarios, which not limited to the COVID-19 pandemic, highlighting systemic inequities embedded within emergency response frameworks. The proposed model framework will enable community managers and service providers to identify vulnerable residents during emergency scenarios. By systematically analysing variations in activity patterns across different vulnerable groups, stakeholders can gain insights into emerging social demands and challenges. This analytical approach enables the development of context-specific resource allocation and support interventions.

In addition, the research critically illuminates the intricate relationships between urban emergency responses, individual well-being, and community resilience. Isolation measures and reduced community engagement can precipitate significant psychological and physiological health challenges, particularly among residents in suboptimal living conditions (e.g., those in substandard housing with insufficient ventilation or lighting provisions) (D'alessandro et al., 2020; Yu et al., 2023). The findings suggest a holistic approach to mitigating these risks: implementing staggered outdoor activities, promoting flexible work arrangements, and developing adaptive community engagement strategies and cross-sectoral policy mixes in disaster and emergency management (Wang et al., 2023c; Zhang et al., 2025). By recognising the potential long-term health implications of prolonged emergency measures, urban managers can design more effective interventions that balance public health benefits with individual psychological needs. Understanding and adapting to these patterns can devise more effective intervention strategies and preventive measures to minimise the adverse health effects of emergencies and potential secondary disasters.

5.2. Limitations and future directions

This section acknowledges the limitations inherent in this study and proposes future directions based on its findings. Firstly, our study relied on online questionnaires for data collection due to the challenges posed by COVID-19 and urban mobility restrictions. However, this approach overlooks residents who lack access to electronic devices or the internet. These marginalised individuals, primarily comprising elderly, low-educated, and low-income populations, are often neglected during emergencies. As the pandemic subsides and urban mobility becomes more flexible, future research could benefit from a combined approach that integrates both online and offline data collection methods to capture a broader spectrum of resident perspectives.

Secondly, the data employed in our case study focused exclusively on employed urban residents. However, beyond them, other residents also suffered from the pandemic. Moreover, the activity patterns of employed residents are also influenced by their non-employed family members. Future studies could benefit from considering non-employed urban residents and widely covering other vulnerable groups such as the elderly, children, people with disabilities, communal dwellers, and small-scale individual entrepreneurs. Revealing the unique activity changes and demands of these groups will be meaningful for tailoring policies and intervention measures to benefit marginalised communities.

Thirdly, our study employed the case of Shanghai during the COVID-19 pandemic and strict mobility restrictions in early 2022. However, residents' activity patterns are significantly influenced by varying economic status and social culture across different regions. In addition, distinct urban emergency conditions pose unique challenges for city management and impact the activity patterns of urban residents differently. The findings from this specific case may not directly apply to other regions or different types of disaster management. Nevertheless, the findings provide a modelling approach for simulating residents' activity patterns. The following studies can subsequently develop localised models and targeted interventions tailored to the demands of local residents.

6. Conclusion

Urban emergency management processes can span days or even months, necessitating the development of people-centric strategies that adapt to changing demands arising from urban population activity patterns and the supply of urban services, facilities, and resources. In this study, we propose a novel modelling framework to explore the activity patterns of diverse residents during urban emergencies, addressing two critical aspects: the heterogeneity of residents' activity patterns during emergencies and the impact of external interventions and policies on these patterns. We calibrated and validated our model using questionnaire data collected during the SARS-CoV-2 pandemic in Shanghai in 2022, focusing on employed local residents. Our analysis revealed several intriguing insights. For instance, women exhibited a lower willingness to engage in outdoor work and domestic tasks. Residents without local household registration (hukou) were more likely to participate in outdoor paid work activity. Additionally, community service participation provided residents with increased outdoor exposure opportunities, thereby reducing health risks associated with self-isolation. The model contributes significantly to urban emergency management by addressing heterogeneous needs, facilitating targeted interventions, and mitigating impacts on residents, the economy, and essential facilities while maintaining quality of life. These findings offer valuable insights for people-centred emergency management at both community- and city-levels, enabling urban managers to develop more effective and equitable response strategies, thereby enhancing overall urban resilience during crises.

ANOVA		
Daytime	F	Sig.
08:00	15.401	0.000
08:30	57.380	0.000
09:00	375.489	0.000
09:30	598.311	0.000
10:00	776.638	0.000
10:30	639.198	0.000
11:00	461.098	0.000
11:30	166.870	0.000
12:00	26.645	0.000
12:30	18.218	0.000
13:00	125.824	0.000
13:30	321.298	0.000
14:00	672.476	0.000
14:30	1200.642	0.000
15:00	1413.106	0.000
15:30	1560.808	0.000
16:00	1288.200	0.000
16:30	586.698	0.000
17:00	226.325	0.000
17:30	85.496	0.000
18:00	31.774	0.000
18:30	15.131	0.000
19:00	17.162	0.000
19:30	14.329	0.000
20:00	9.274	0.002
20:30	7.283	0.007
21:00	12.912	0.000
21:30	8.403	0.004

CRediT authorship contribution statement

Qian-Cheng Wang: Writing – original draft, Visualization, Validation, Software, Methodology, Conceptualization. **Ping He:** Writing – original draft, Visualization, Validation, Investigation. **Yibin Li:** Validation, Resources, Investigation, Data curation. **Yuting Hou:** Validation, Resources, Funding acquisition. **Yi Izzy Jian:** Writing – review & editing, Validation, Resources. **Xuan Liu:** Writing – original draft, Methodology, Conceptualization.

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.

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Data availability

Data will be made available on request.

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