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Built environment factors moderate pandemic fatigue in social distance during the COVID-19 pandemic: A nationwide longitudinal study in the United States

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HIGHLIGHTS

- Pandemic fatigue in social distance continuously worsened over time.
- A sharp increase of pandemic fatigue occurred after the vaccination program began.
- Greenspace and urbanicity levels moderated pandemic fatigue.
- Areas with more greenness experienced lower pandemic fatigue.
- Areas with higher urbanicity levels experienced lower pandemic fatigue.

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ABSTRACT

Non-pharmaceutical interventions (NPIs) remain some of the most effective measures for coping with the ever-changing coronavirus disease 2019 (COVID-19) pandemic. Pandemic fatigue, which manifests as the declined willingness to follow the recommended protective behaviors (e.g., keeping social distance policies, wearing masks), has commanded increasing attention from researchers and policymakers after the prolonged NPIs and COVID-19 worldwide. However, long-term changes in pandemic fatigue are not well understood, especially amidst the ever-changing pandemic landscape. Built environment factors have been shown to positively affect mental and physical health, but it is still unclear whether built environments can moderate pandemic fatigue. In this study, we used Google mobility data to investigate longitudinal trends of pandemic fatigue in social distance since the onset of NPIs enforcement in the United States. The results indicated that pandemic fatigue continuously worsened over nearly two years of NPIs implementation, and a sharp increase occurred after the vaccination program began. Additionally, we detected a significant moderation effect of greenspace and urbanicity levels on pandemic fatigue. People living in areas with high levels of greenness or urbanicity experienced lower levels of pandemic fatigue. These findings not only shed new light on the effects of greenness and urbanicity on COVID-19 pandemic fatigue, but also provide evidence for developing more tailored and effective strategies to cope with pandemic fatigue.

1. Introduction

1.1. Non-pharmaceutical interventions remain critical measures controlling COVID-19 pandemic

To curb the rapid spread of coronavirus disease 2019 (COVID-19), governments and health authorities across the globe have implemented a wide range of control policies, including border restrictions, mask mandates, and various social distance policies (Flaxman et al., 2020; Hale et al., 2021). Such non-pharmaceutical interventions (NPIs) have effectively constrained COVID-19 spread by both reducing human mobility and enhancing individual health-protective behaviors (Bo

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et al., 2021; Glogowsky, Hansen, & Schächtele, 2021; Wellenius et al., 2021), even with the accompanying social and economic disruptions (Bonaccorsi et al., 2020; Lai et al., 2020). Although the vaccination programs have been gradually implemented worldwide from year 2021, several countries that lifted NPIs witnessed subsequential surges in COVID-19 cases, putting severe strains on population health and medical resources (Al-Tammemi, Tarhini, & Akour, 2021; Li et al., 2021).

Integrating NPIs and vaccination remains indispensable strategy for managing the ongoing waves and virus variants of COVID-19 (Iftekhar et al., 2021; Kwon et al., 2021). The latest evidence has shown that vaccination alone (i.e., without NPIs) often has adverse consequence (Moore, Hill, Tildesley, Dyson, & Keeling, 2021). Optimistic predictions showed that at least 21,400 excessive deaths would have occurred in the UK without NPIs, even with the assumption of reaching an 85 % vaccination rate (Moore et al., 2021). When considering the emergence and spread of powerful virus variants (e.g., Delta and Omicron) (Karim & Karim, 2021) and the lower vaccination rates and weak medical system in developing countries (Perveen, Akram, Nasar, Arshad-Ayaz, & Naseem, 2021), enforcing appropriate intensity NPIs remains an effective strategy for handling challenges related to the COVID-19 pandemic. In the long term, it may remain effective in future pandemics.

1.2. Pandemic fatigue represents a serious concern after over 2 years of ongoing COVID-19 outbreaks

However, in the context of over 2 years of struggling with COVID-19, pandemic fatigue has emerged and commanded the attention of researchers and government authorities (Haktanir, Can, Seki, Kurnaz, & Dilmaç, 2021; MacIntyre et al., 2021; Michie, West, & Harvey, 2020). The World Health Organization (WHO) defines pandemic fatigue as demotivation to follow the recommended protective behaviors over time, which mainly manifests as the declined willingness to follow the individual-level health behavior (e.g., wearing mask, washing hands) and keep social distance policies (e.g., reducing non-essential visits, stay-at-home orders) (WHO, 2020). The main causes of pandemic fatigue include the increasing levels of mental and physical exhaustion (e.g., stress, anxiety, depression, and decreased motivation) after the long-term pandemic, lenient NPIs enforcement, low risk perception, or individual negative experience and expectation (e.g., losing job or income) (Haktanir et al., 2021; Öksüz, Kalkan, Can, & Haktanir, 2021; Queen & Harding, 2020). It is not only a threat to the individuals' health but also presents a major risk and challenge to pandemic prevention and control before a pandemic is contained (Al-Tammemi et al., 2021; Iftekhar et al., 2021).

Some emerging studies have explored the pandemic fatigue related issues (Delussu, Tizzoni, & Gauvin, 2022; Haktanir et al., 2021; MacIntyre et al., 2021; Petherick et al., 2021; Shearston, Martinez, Nunez, & Hilpert, 2021). There are various terms used in these studies, such as "social-distancing fatigue" (Shearston et al., 2021), "behavioral fatigue" (Michie et al., 2020), "pandemic burnout" (Queen & Harding, 2020), and "pandemic fatigue", which is the most frequently used and endorsed by WHO.

As different terms hint, pandemic fatigue is a complex behavioral construct, which mainly involves two distinctive behaviors: 1) individual-level protective behaviors (Haktanir et al., 2021; MacIntyre et al., 2021), such as wearing masks, washing hands, or practicing hygiene etiquette; 2) keeping social distance policies (Delussu et al., 2022; Shearston et al., 2021), such as reducing non-essential travel, stay-at-home orders (Fig. 1).

Some studies explored the pandemic fatigue in individual-level protective behaviors often with self-reported survey data. For example, a cross-sectional study conducted in Turkey in November 2020 examined the state of pandemic fatigue and its relationship to the bio-psychosocial nature of humans (Haktanir et al., 2021). One third of the participants reported a decline in protective behaviors from that during the onset of the pandemic, and the fear of coronavirus and intolerance to uncertainty were found to directly affect pandemic fatigue. Similarly, another study conducted in five cities in different countries reported that pandemic fatigue, measured by mask use, was significantly associated with younger age groups, low perceived COVID-19 severity, and declines in COVID-19 prevalence (MacIntyre et al., 2021). While survey data could directly depict such protective behaviors at individual level, it is hard to track changes in pandemic fatigue over long period of time.

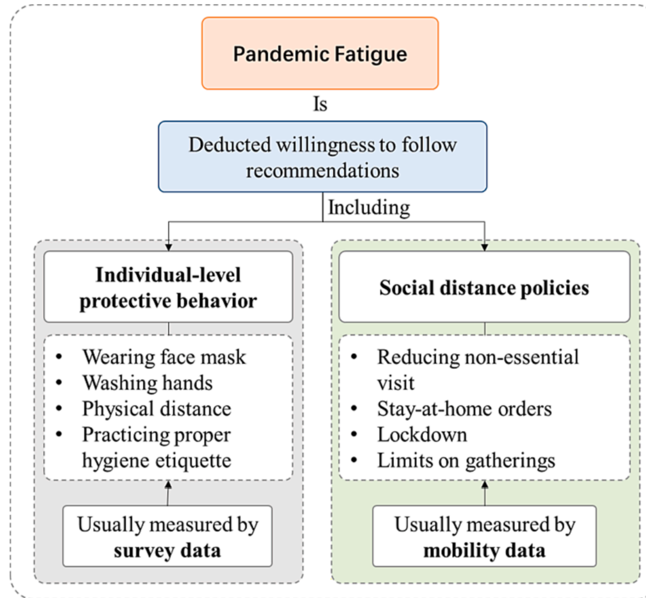

Fig. 1. The main behavioral manifests of pandemic fatigue.

Some other studies explored the pandemic fatigue in social distance often with mobility large data. Observing longitudinal changes in non-essential mobility through mobile location data (e.g., GPS data, Google mobility data, or traffic data) is a valid option assess to the level of compliance with social distance policies (Lucchini et al., 2021; Petherick et al., 2021; Shearston et al., 2021). For example, Petherick et al. (2021) investigated changes in protective behaviors and mobility in 14 countries from March to December 2020 using both self-reported data and Google mobility data. The findings have shown that adherence to low costs behaviors, such as wearing mask, presented a linear rising trend over time. Conversely, a significant increase in high cost behaviors (e.g., visits to retail and recreation locations) was identified over time, despite controlling for policy strength, revealing a gradual reduction in adherence to social distance policies (Petherick et al., 2021). Besides, the real-time traffic data, as a proxy for human mobility, was also used to measure the pandemic fatigue in social distance (Shearston et al., 2021).

To examine the long-term longitudinal change in pandemic fatigue, this study focuses on pandemic fatigue in social distance (Green part in Fig. 1) given the and availability and superiority of mobility large data. The fatigue in individual-level protective behaviors such as wearing masks was not considered due to the data unavailability.

1.3. Built environment factors may be a potential moderator for pandemic fatigue

Strong evidence suggests that certain built environment factors, such as greenspace and urban density, can significantly affect health outcomes (Fong, Hart, & James, 2018; Jackson, 2003) and modulate rule-adherence behaviors (Taylor, Kuo, & Sullivan, 2002). Studies before the pandemic reported that more visual or physical exposure to urban greenspace could significantly improve mental health. Living in areas with more accessible greenspace contributes to restoration from mental fatigue (Jiang, Schmillen, & Sullivan, 2018; Kaplan, 2001; Li & Sullivan, 2016) and reductions in stress levels or depression (Hartig, Mitchell, Vries, & Frumkin, 2014; Jiang, Li, Larsen, & Sullivan, 2016; Richardson, Pearce, Mitchell, & Kingham, 2013), which suggests that greenspace may potentially moderate pandemic fatigue by mitigate such negative psychological effect. During the pandemic, greenspaces including urban parks and forests became more critical elements of living environments for releasing both mental and physical stress derived from increasing COVID-19 case numbers and NPIs stringency (Lu, Chen, et al., 2021). Substantial increases in visits to greenspaces were reported by several studies after NPIs implementation (Lu, Zhao, Wu, & Lo, 2021; Venter, Barton, Gundersen, Figari, & Nowell, 2020; Venter, Barton, Gundersen, Figari, & Nowell, 2021). Visiting greenspace became an essential activity to enhance health behaviors during the pandemic period compared with the non-pandemic periods (Ugolini et al., 2020).

More contact with greenspace has a positive effect on improving self-discipline behaviors. An US study examined the relationship between greenspace and the self-discipline behaviors of boys and girls living in high-rise buildings and found that girls living with more window views of nature had better self-discipline (Taylor et al., 2002). Sufficient self-discipline is essential for the long-term adherence to various policies, which may affect pandemic fatigue. Such positive effects of greenspace could potentially mitigate pandemic fatigue by alleviating its mental and physical manifestations.

Additionally, evidence also suggests urban density affects risk perceptions. A recent study conducted in the US found that people living in dense urban areas and metropolitan cities had higher risk perceptions and more concerns towards the COVID-19 pandemic (Chauhan et al., 2021). Such different attitudes in urban and rural areas may lead different levels of pandemic fatigue, with higher risk-perception areas has a relative lower pandemic fatigue in social distance. Theoretically, dense urban areas should witness a relatively high infection rate in a pandemic due to the inevitable high risk of close contact. However, a negative relationship or no relationship between density and infection rate was reported in several studies (Credit, 2020; Liu, 2020; Tribby & Hartmann, 2021). This may be attributable to stricter policies, higher risk awareness, or better policy adherence in urban areas (Ibrahim, Eid, Mostafa, Bishady, & Elghalban, 2020).

1.4. Research gaps and hypotheses

In summary, there are two major research gaps. First, little is known about longitudinal changes in pandemic fatigue after two years of NPIs implementation. In COVID-19-related research and NPIs implementation processes, NPIs tend to be treated as a static variable, and NPIs efficiency is usually assumed to remain constant over time (Petherick et al., 2021). Further, the latest research on longitudinal changes in pandemic fatigue was conducted before 2021, when the more powerful variants (e.g., Delta and Omicron) had yet to emerge, and large-scale vaccination programs were not yet underway in developing countries. This leads us to question how the trend in pandemic fatigue has developed under such an uncertain and turbulent backdrop in 2021. Overlooking pandemic fatigue may lead to misjudgments about the pandemic situation and even a delay in pandemic prevention and control. Therefore, gaining a deep understanding of pandemic fatigue over a longer timescale is urgently needed to inform policy decision-making and cope with the changing pandemic situation.

Additionally, it remains unclear whether built environment factors (e.g., green space and urban density) can moderate pandemic fatigue. Although existing evidence points toward a relationship between pandemic fatigue and built environment factors, we still know little about variations in pandemic fatigue levels in areas with different built environments. Exploring this relationship is essential for developing more tailored and effective strategies to cope with pandemic fatigue.

We formed two hypotheses to address these research gaps:

Hypothesis 1: Pandemic fatigue in social distance is worsening over long periods of NPIs implementation.

This hypothesis is based on the current research output and news reports about vaccination. Andersson, Campos-Mercade, Meier, and Wengström (2020) found that vaccine information reduces voluntary social distance, adherence to hygiene guidelines, and willingness to stay at home. As the vaccination rate continues to increase worldwide, the risk awareness of the public may continuously decrease. Policy compliance may also decline even as the number of infections continues to rise. Hence, increased vaccination rates may worsen pandemic fatigue.

Hypothesis 2: Pandemic fatigue in social distance could be significantly moderated by certain built environment factors.

Given the impact of built environment factors on health outcomes and rule-adherence behaviors, we hypothesize that pandemic fatigue in social distance caused by prolonged NPIs implementation is moderated by built environment factors (Fig. 2).

This hypothesis is based on two moderation pathways. The first pathway is the influence of built environments on mental and physical health. Built environment factors (e.g., greenspace) may alleviate the negative mental emotions and physical exhaustion caused by prolonged NPIs enforcement. Greenspaces not only improve recovery from mental fatigue but also promote physical activity, which could help maintain better mood states (Barton & Pretty, 2010; Berger & Motl, 2000; Fox, 1999) and promote positive lifestyles and emotions (Hogan, Catalino, Mata, & Fredrickson, 2015). These benefits could contribute to reducing behavioral fatigue and strengthen motivation to comply with NPIs.

The second pathway involves affecting self-discipline performance and risk perceptions. Self-discipline plays a significant role in compliance with rules and regulations, including social distance policies. People living near greenspaces may have better self-discipline performance to comply with NPIs and experience lower pandemic fatigue levels than those with less access to greenspaces. Besides, the above-mentioned evidence also shown that people living in urban areas have higher risk perceptions towards the pandemic. As such, pandemic fatigue in social distance could be moderated by these built environment characteristics. These ideas prompted us to investigate whether the magnitude of pandemic fatigue varies among people living in different built environments.

To address the above gaps, we first investigated how pandemic fatigue has developed in the US since the onset of NPIs implementation. The longitudinal evolution pattern of pandemic fatigue during this period was predicted and summarized. Second, we examined the moderation effect of built environment factors on pandemic fatigue via mixed-effects modeling. The potential mechanisms underlying the moderation effects were also discussed.

2. Material and methods

2.1. Study area

Since March 2020, various NPIs have been implemented in the US to control the spread of COVID-19. People living in different states experienced continuously changing NPIs for 2 years. To examine the pandemic fatigue situation in the US, we choose counties, which are fundamental administrative boundaries as the basic unit of analysis. A total of 3,108 counties in the contiguous US were investigated.

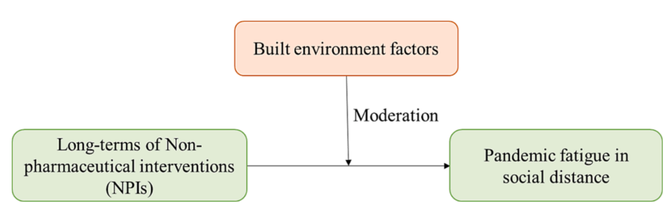

Fig. 2. The moderation effect of built environment factors on pandemic fatigue in social distance.

2.2. Measuring pandemic fatigue in social distance using mobility data

As we mentioned in section 1.2, considering the availability and superiority of mobile location data in conducting longitudinal analysis on pandemic fatigue, the scope of pandemic fatigue in this study was defined as the pandemic fatigue in social distance aspect (Green part in Fig. 1).

We investigated longitudinal changes in pandemic fatigue in social distance during the NPIs implementation period from March 2020 to October 2021 in the contiguous US. Following previous studies (Delussu et al., 2022; Petherick et al., 2021; Zhanwei et al., 2021), pandemic fatigue was assessed using longitudinal mobility data from Google Community Mobility Reports (Google, 2021). Evidence has shown that human mobility data is a vital proxy measure for social distance policies' efficiency (Abouk & Heydari, 2021; Vokó & Pitter, 2020; Wellenius et al., 2021). Specifically, many NPIs mainly control virus transmission by reducing human mobility (Kraemer et al., 2020; Nouvellet et al., 2021). Assuming that the willingness to comply with NPIs and other conditions (e.g., NPIs stringency level) are constant in a pandemic, human mobility will remain stable. We can identify the existing of a pandemic fatigue in social distance when mobility partially or fully rebounds, given other conditions remain unchanged. Therefore, pandemic fatigue in social distance can be assessed by changes in mobility after controlling for the NPIs stringency level and other factors (Petherick et al., 2021). Hence, the mobility data could provide a low-cost, large-scale, and longitudinal measurement of social distance behaviors, an essential aspect of pandemic fatigue.

The Google Community Mobility Reports contain six types of mobility data, including retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential. The values of this dataset represent the change of visits compared to the baseline in each type of destinations. We choose the retail and recreation mobility data, which includes places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters, as a primary measure. The mobility of such places represents non-essential travel behaviors, providing a proxy for the degree of following social distance policies. We also provided analysis for three other types of mobility in the appendix, though three other types of mobility may have some limitations to assess pandemic fatigue in social distance. For example, workplace/residential mobility may be affected by employers' decisions (e.g., decision to have employees work from home), park mobility may be subject to weather/climate conditions, and grocery and pharmacy mobility are affected by essential needs.

The retail and recreation mobility data from March 2020 to October 2021 were divided into 30-day intervals. For each interval, the average values of retail and recreation mobility were calculated for each county. Therefore, each county in the US had 19 mobility data points. Each county's baseline mobility value (mobility at the initial stage) was defined as the first 30-day interval value after NPIs implementation, representing the initial efficiency of NPIs. Pandemic fatigue, or the magnitude of mobility change, was measured as changes in retail and recreation mobility compared with the baseline. In other words, pandemic fatigue of the n^{th} time interval in county m was calculated as the mobility in the n^{th} time interval minus the baseline value in county m. Hence, the dependent variable, i.e., pandemic fatigue, was time-varying.

2.3. Measuring NPIs stringency

To control the effects of different NPIs stringency levels on human mobility change, we used the stringency index from OxCGRT data as a predictor (Hale et al., 2021). The index was daily basis in state level, calculated according to seven types of containment policies including closing schools, closing workplaces, public event cancelations, gathering restrictions, closing public transport, stay-at-home requirements, and restrictions to internal movement and international travel. Consistent with the pandemic fatigue calculation method, we calculated the average stringency index in each 30-days interval for each state. The change in NPIs stringency at each time interval in each state was calculated as the stringency index value in the n^{th} time interval minus the baseline value in state m. The stringency index was also time-varying.

2.4. Built environment factors

2.4.1. Greenspace

The overall greenspace level for each county was assessed using the average normalized difference vegetation index (NDVI) values in 2020 (Figure S1 in the appendix). The data source was satellite imagery at 30-m resolution from Google Earth Engine (Gorelick et al., 2017).

2.4.2. Urbanicity level

According to the National Center for Health Statistics Urban-Rural Classification Scheme for Counties in the US (NCHS, 2017), we classified the urbanicity level of each county into six classes, with level 1 being the most urbanized and level 6 being the most rural (Figure S2).

2.5. Covariates

2.5.1. Vaccination rate

Research has indicated that vaccinated people may be more likely to underestimate the infection risk and reduce adherence to NPIs (Andersson et al., 2020). Hence, the level of vaccination rate may influence pandemic fatigue to a certain extent. The vaccination rate was calculated as the percentage of fully vaccinated people at the county level. Consistent with the calculation methods of pandemic fatigue and stringency index, the vaccination rate was also time-varying.

2.5.2. Confirmed cases

Risk perception is a critical factor affecting human mobility during the COVID-19 pandemic (Chan, Skali, Savage, Stadelmann, & Torgler, 2020). People may increase protective behaviors and voluntarily reduce mobility when the case numbers increase. Hence, we chose change of the mean daily confirmed COVID-19 cases at county level compared to value in baseline, as a measure of pandemic severity, as the control variable.

2.5.3. Socio-economic and other factors

Additionally, we adjusted for potential socio-economical covariates in each county, including age, income, Gini index (a measure of income inequality), and race. Political (voting percentage for the Democracy), air quality ($PM_{2.5}$), temperature, and sun exposure factors, which may potentially affect mobility, were also included in the model. The calculation method and data source of these variable was described in supplementary Table S1, and the descriptive statistics for them were presented in Table S2.

2.6. Model selection

Given the longitudinal structure (repeated measures in time, nested within different counties) of the data, we used mixed-effects models to model longitudinal changes in pandemic fatigue and examine how the built environment factors moderate the effects of NPIs on pandemic fatigue. The level of pandemic fatigue, represented by changes in human mobility, was the dependent variable. The main explanatory variables were the NPIs stringency index and built environment factors. The moderation effect of built environment factors on the effect of NPIs stringency on pandemic fatigue was examined using interaction terms (NPIs $\times$ built environment factors). Other covariates were also considered in our models.

First, we modeled pandemic fatigue using the stringency index and a series of covariates (Model 1). A quadratic time trend (time-squared) was included in the model to assess the non-linear global patterns of pandemic fatigue. Second, we added the built environment factors, NDVI, and urbanicity levels to the model (Model 2). Third, interaction terms representing NPIs stringency and the built environment factors were also added to the model (Model 3) to examine the moderation effect.

Mixed-effects models have been widely applied in longitudinal data analysis. Mixed-effects models are robust in the face of missing data and can also model non-linear (e.g., quadratic and cubic) changes over time. The time interval data were nested within counties, and county data were nested within states. The equation is as follows (Laird & Ware, 1982):

$$\mathbf{Y}_i = \mathbf{X}_i\boldsymbol{\beta} + \mathbf{Z}_i\mathbf{b}_i + \varepsilon_i$$

$$\mathbf{b}_i \ \mathbf{N}_q(0, \Psi)$$

$$\varepsilon_i \ \mathbf{N}_{n_i}(0, \boldsymbol{\sigma}^2\Lambda_i)$$

$\mathbf{Y}_i$ is the $n_i \times 1$ response vector for pandemic fatigue observations in the i^{th} county, n_i is the number of observations for the i^{th} county. $\mathbf{X}_i$ is the $n_i \times p$ model matrix for the fixed effects for pandemic fatigue in county i, and p is the number of predictors, including the intercepts (e.g., time interval, time-squared [representing a non-linear quadratic trend in pandemic fatigue over time], stringency index, built environment factors, interaction terms, vaccination rate, and socio-economic factors) for the fixed effects. $\boldsymbol{\beta}$ is the $p \times 1$ vector of the fixed-effect coefficients, our focus of interest. $\mathbf{Z}_i$ is the $n_i \times q$ model matrix for the random effects for pandemic fatigue observations in county i, and q is the number of random effects, including the intercept, time and time-squared in each county. $\mathbf{b}_i$ is the $q \times 1$ vector of random-effect coefficients for county i. ε_i is the $n_i \times 1$ vector of errors for pandemic fatigue observations in county i. Ψ is the $q \times q$ covariance matrix for the random effects. $\boldsymbol{\sigma}^2\Lambda_i$ is the $n_i \times n_i$ covariance matrix for the errors in county i.

All analyses were conducted in R v4.1 (Team, 2021) using the lmer4 package (Bates, Mächler, Bolker, & Walker, 2014).

3. Results

3.1. Pandemic fatigue longitudinal trend

The dotted line in Fig. 3 shows the overall longitudinal pattern of pandemic fatigue levels since NPIs implementation after controlling for NPIs stringency, built environment factors, and other covariates. Generally, an upward trend with two peaks was observed during the 18 months, indicating that pandemic fatigue increased over time. The peaks occurred at around the 6th and 15th months, respectively. The 15th month (June 2021) was 6 months after the vaccination program began in the US. Pandemic fatigue showed a slight downward trend after the 15th month. The pandemic fatigue trend calculated by other types of mobility data (e.g., residential, work, or park mobility) also presented similar patterns (See Supplementary Figures S3, S4, and S5). For example, a continuously decreased trend in the change of residential mobility was observed, implying that containment and closure policies were becoming less effective, that was the worsen pandemic fatigue in social distance. Similarly, the change of work mobility presented an opposite upward trend, also showing that pandemic fatigue continuously worsened.

Different urbanicity levels had different pandemic fatigue levels, although the general trends followed the overall pandemic fatigue level. The higher the urbanization level, the lower the pandemic fatigue. In other words, the most urbanized areas (urbanicity level 1) consistently maintained the lowest levels of pandemic fatigue, and the most rural areas (level 6) experienced the highest pandemic fatigue levels. Differences in pandemic fatigue across the urbanicity levels became apparent at the onset of the vaccination program in the 9th month.

Further, to explore whether pandemic fatigue situation in each urbanization level differs under different NDVI levels, we classified counties as having low or high greenness according to the median NDVI values in each urbanicity level. The longitudinal pandemic fatigue trends in counties with low and high greenness in each urbanicity level are presented in Fig. 4. Except in the urbanicity level 1, people living in areas with low greenness experienced higher pandemic fatigue than those living in areas with high greenness in the same urbanicity level. The disparity in pandemic fatigue levels between high and low greenness regions became more prominent over time.

3.2. The moderation effect of built environment factors

Table 1 compares the fits of the three models (described in section 2.7). The model fit was significantly improved by incrementally adding built environment factors and interaction terms into Models 2 and 3. Specifically, the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and residual deviance of Model 2 were lower

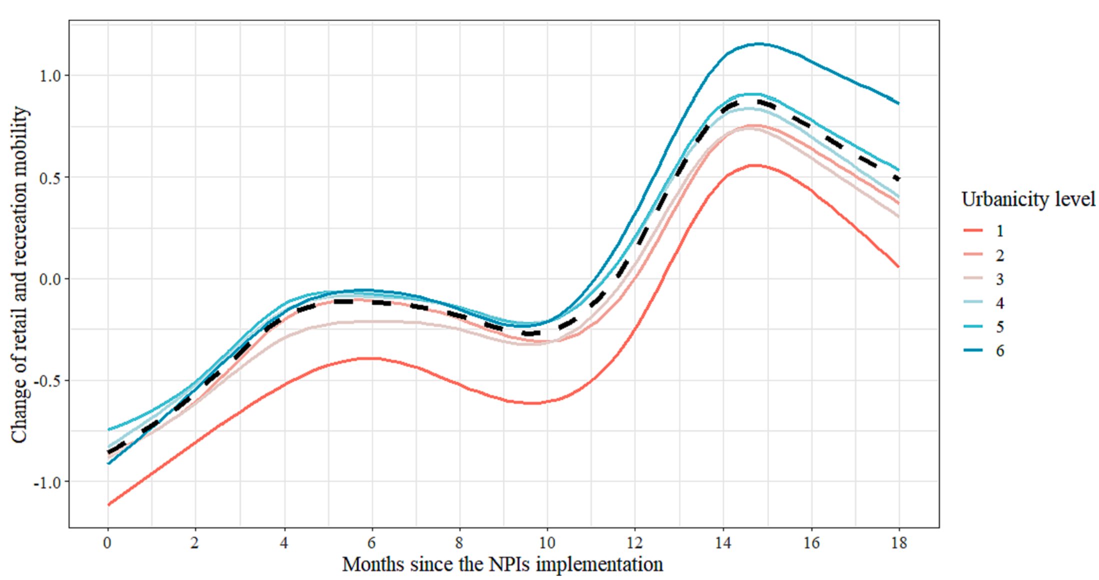

Fig. 3. Longitudinal pandemic fatigue trends in different urbanicity levels over the 18 months since NPIs implementation. (Time 0 represents the baseline period (the first 30 days after NPIs implementation). Urbanicity level 1 represents the most urbanized areas and level 6 represents the most rural areas.)

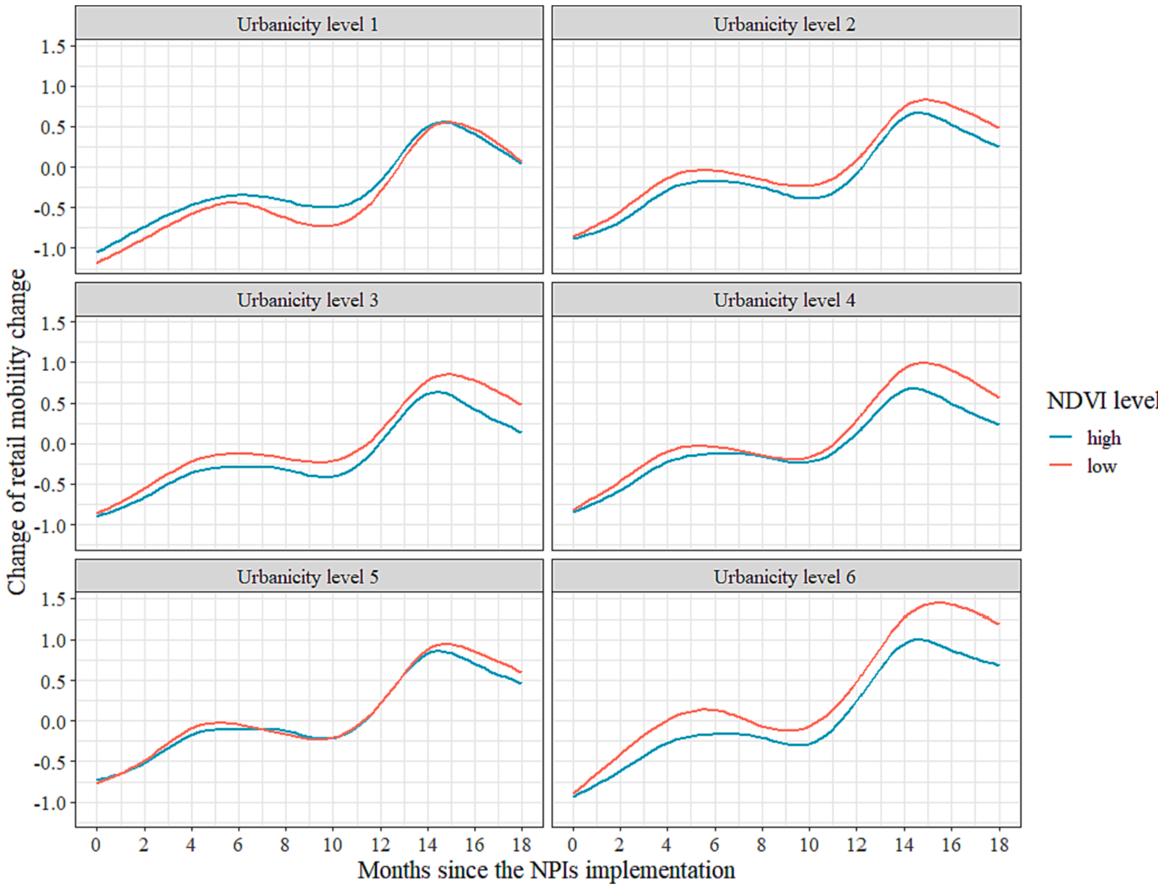

Fig. 4. Longitudinal pandemic fatigue trends in areas with high or low NDVI in six urbanicity levels over the 18 months since NPIs implementation.

Table 1
Model comparison.

	Marginal R^2	AIC	BIC	logLik	deviance	Chisq	Df	Pr(>Chisq)
Model 1	0.651	62,606	62,783	−31282	62,564			
Model 2	0.658	62,451	62,679	−31199	62,397	166.69	6	<0.001
Model 3	0.666	61,994	62,272	−30964	61,928	469.64	6	<0.001

Note: AIC, akaike information criterion; BIC, bayesian information criterion. Model 1 is using the NPIs stringency index and a series of covariates to model pandemic fatigue. In Model 2, the built environment factors, NDVI, and urbanicity levels, were added to the model. In Model 3, interaction terms representing NPIs stringency and the built environment factors were also added to the model to examine the moderation effect.

than those of Model 1, and the same values in Model 3 were lower than those in Model 2. The analysis of variance also detected significant differences between Model 1 and Model 2 and between Model 2 and Model 3. After adding the interaction terms between built environment factors and NPIs stringency, the marginal R^2 of Model 3 was 0.666, 0.015 higher than that of base Model 1 ($R^2 = 0.651$).

Interaction terms

The significant interaction terms in Model 3 confirmed that the built environment factors moderate the effect of NPIs on pandemic fatigue (Table 2). Specifically, the NDVI enhanced the negative relationship between stringency index and mobility change, and the urbanicity level weakened the relationship. To clearly illustrate the interaction term of two continuous variables (NDVI × stringency index), we followed the spotlight analysis method In Fig. 5 (Aiken, West, & Reno, 1991; UCLA, 2022). We picked three representative values, including the mean level of NDVI, one standard deviation up or below the mean level of NDVI respectively, to estimate the slope of stringency index with mobility. It shows that compared with high NDVI areas, mobility in low NDVI areas rebounded faster with the decrease in NPIs stringency. Similarly, Fig. 6 shows that compared with high-urbanicity areas, mobility in low-urbanicity areas (level 6 represents the most rural areas) rebounded faster with the decrease in NPIs stringency.

Time and time-squared

The time and time-squared terms were consistently significant in all models, which further demonstrated the non-linear longitudinal changes in pandemic fatigue (Figs. 3 and 4). The positive estimated coefficient of time illustrated that pandemic fatigue increased over time. Furthermore, the negative coefficient of the quadratic time term indicates the rate of pandemic fatigue increase also increased over time.

Covariates

Both the stringency index and the number of confirmed cases had negative effects on pandemic fatigue. Pandemic fatigue increased as NPIs stringency and COVID-19 case numbers decreased. Consistent with our hypothesis, the vaccination rate had a positive impact on pandemic fatigue.

4. Discussion

Prolonged NPIs implementation in response to the ever-changing COVID-19 pandemic has caused varying degrees of pandemic fatigue

Table 2
Pandemic fatigue regression results.

	Model 1			Model 2			Model 3		
Predictors	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p
(Intercept)	−0.12	(−0.15,−0.09)	<0.001	−0.14	(−0.25,−0.03)	0.016	−0.35	(−0.48,−0.23)	<0.001
Time	1.13	(1.10,1.16)	<0.001	1.12	(1.09,1.15)	<0.001	1.13	(1.11,1.16)	<0.001
Time-squared	−1.61	(−1.65,−1.56)	<0.001	−1.59	(−1.63,−1.55)	<0.001	−1.61	(−1.66,−1.57)	<0.001
NPIs stringency index	−0.34	(−0.35,−0.33)	<0.001	−0.34	(−0.36,−0.33)	<0.001	−0.12	(−0.17,−0.07)	<0.001
Vaccination rate	0.74	(0.72,0.76)	<0.001	0.73	(0.71,0.75)	<0.001	0.74	(0.72,0.76)	<0.001
Confirmed cases	−0.02	(−0.02,−0.01)	<0.001	−0.02	(−0.02,−0.01)	<0.001	−0.02	(−0.02,−0.01)	<0.001
Income	0.02	(0.00,0.04)	0.043	0.01	(−0.01,0.04)	0.218	0.01	(−0.02,0.03)	0.558
Age	0.07	(0.05,0.09)	<0.001	0.09	(0.07,0.11)	<0.001	0.09	(0.07,0.11)	<0.001
Race	−0.01	(−0.04,0.01)	0.351	0	(−0.03,0.03)	0.975	−0.01	(−0.03,0.02)	0.704
Political	0.04	(0.01,0.06)	0.004	0.02	(−0.00,0.05)	0.084	0.02	(−0.00,0.05)	0.058
Temperature	−0.14	(−0.17,−0.11)	<0.001	−0.19	(−0.22,−0.16)	<0.001	−0.19	(−0.22,−0.16)	<0.001
$PM_{2.5}$	0.03	(0.01,0.05)	0.001	0.02	(−0.00,0.04)	0.119	0.02	(−0.00,0.04)	0.124
Sun exposure	−0.08	(−0.10,−0.06)	<0.001	−0.03	(−0.06,−0.00)	0.033	−0.02	(−0.05,0.01)	0.188
Gini index	0	(−0.02,0.02)	0.809	0	(−0.02,0.03)	0.687	0	(−0.02,0.03)	0.743
NDVI				0.06	(0.03,0.08)	<0.001	0.01	(−0.02,0.03)	0.658
Urbanicity level 2				0.08	(−0.03,0.19)	0.162	0.27	(0.14,0.39)	<0.001
Urbanicity level 3				0.1	(−0.01,0.21)	0.082	0.22	(0.10,0.35)	0.001
Urbanicity level 4				0.07	(−0.05,0.19)	0.236	0.24	(0.11,0.37)	<0.001
Urbanicity level 5				0.12	(0.01,0.24)	0.035	0.37	(0.24,0.50)	<0.001
Urbanicity level 6				−0.16	(−0.28,−0.04)	0.01	0.17	(0.03,0.30)	0.015
NDVI × Stringency index							0.07	(0.06,0.08)	<0.001
Urbanicity level 2 × Stringency index							−0.2	(−0.26,−0.14)	<0.001
Urbanicity level 3 × Stringency index							−0.15	(−0.21,−0.09)	<0.001
Urbanicity level 4 × Stringency index							−0.19	(−0.25,−0.13)	<0.001
Urbanicity level 5 × Stringency index							−0.27	(−0.33,−0.21)	<0.001
Urbanicity level 6 × Stringency index							−0.42	(−0.48,−0.36)	<0.001

Notes: CI, confidence intervals, NDVI, normalized difference vegetation index.

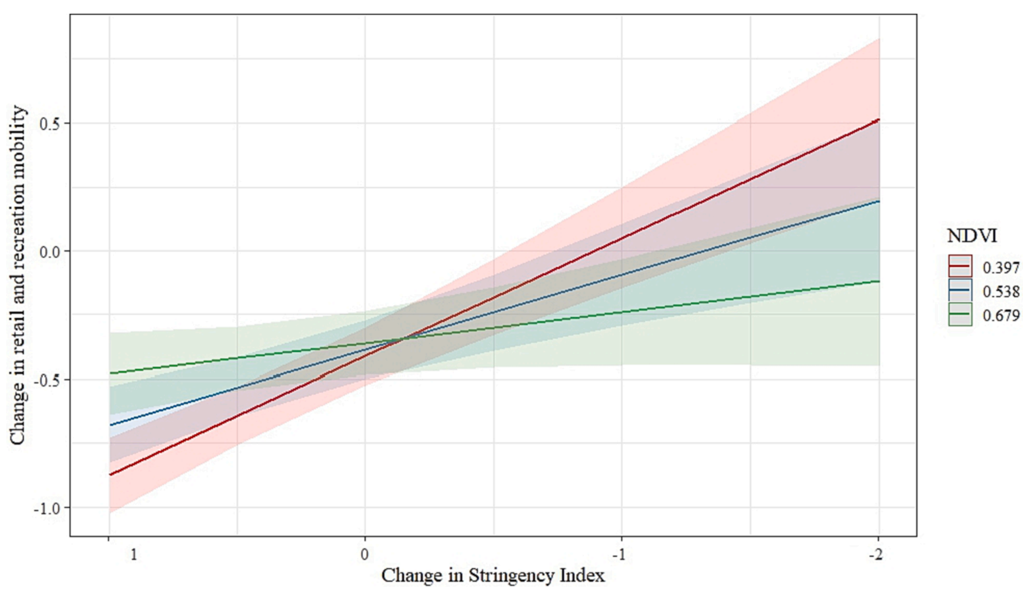

Fig. 5. The NDVI moderates the effect of NPIs stringency on mobility. (0.538 is the mean value of NDVI, 0.397 and 0.679 are one standard deviation below and up the mean level of NDVI. As NPIs stringency decreased (from left to right), mobility rebounded faster in low-NDVI areas than in high-NDVI areas.).

worldwide (Al-Tammemi et al., 2021; Haktanir et al., 2021; MacIntyre et al., 2021; Petherick et al., 2021). In this study, we explored longitudinal pandemic fatigue trends in the US over 18 months. We also investigated the moderation effect of built environment factors using mixed-effects models. Three major findings were revealed.

First, pandemic fatigue continuously worsened over the nearly 2-year NPIs implementation period, showing an upward trend with two peaks. Our results echo one previous study (Petherick et al., 2021); the adherence to NPIs decreased over time. We tentatively propose three potential causes for the continuously worsening pandemic fatigue. 1) The accumulating mental burden and stress over a long period of NPIs implementation can exacerbate pandemic fatigue. Substantial evidence has shown that NPIs cause psychological problems such as depression, generalized anxiety disorder, stress, and exhaustion (Benke, Autenrieth, Asselmann, & Pané-Farré, 2020; Holmes et al., 2020; Marroquín, Vine, & Morgan, 2020). Experiencing negative emotions over a long period is likely to decrease motivation to adhere to NPIs. 2) Accumulating economic pressure may lead to reductions in NPIs adherence. The COVID-19 pandemic triggered an overwhelming economic shock worldwide (Ibn-Mohammed et al., 2021); people experiencing heavy economic burden showed a strong desire to return to normal life (Abu-Farha, Alzoubi, & Khabour, 2020). 3) Frequent changes in NPIs may worsen

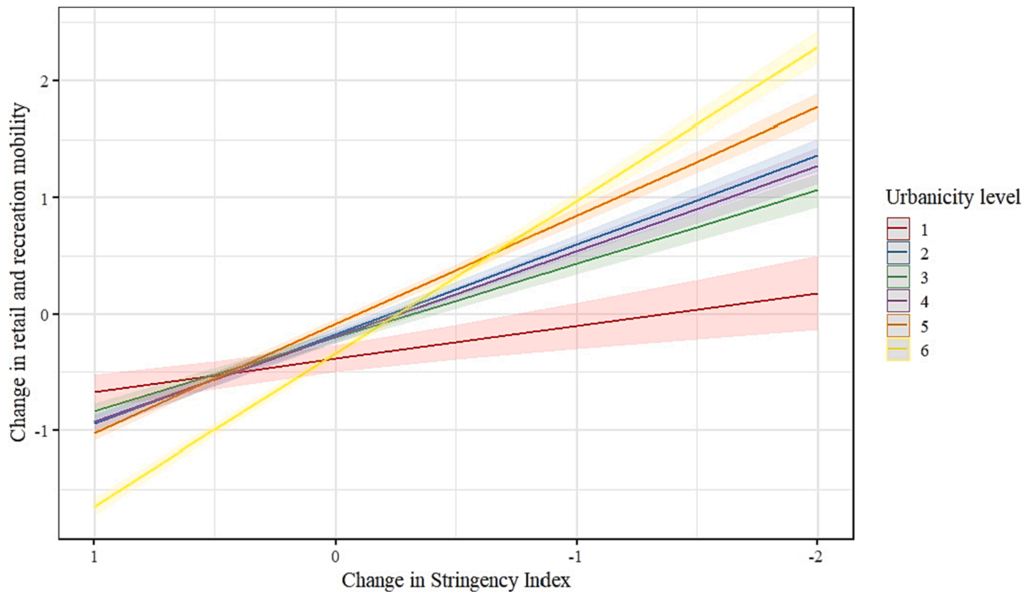

Fig. 6. Urbanicity levels moderate the effect of NPIs stringency on mobility. (As NPIs stringency decreased (from left to right), mobility rebounded faster in rural areas (level 6 represents the most rural areas) than in urbanized areas (level 1 represents the most urbanized areas).

pandemic fatigue. In many places, NPIs were regularly adjusted to cope with the dynamic pandemic situation. The psychological fatigue makes it challenging for the public to keep up with frequent changes in NPIs policies over such a long period (Li et al., 2021).

In addition, we observed two dips in pandemic fatigue during the 4th to 7th and 15th to 18th months after NPIs implementation. The increased infection risk during these two periods may have strengthened NPIs adherence behaviors. Comparing the mean daily new infections and pandemic fatigue levels in the US counties (Fig. 7), an exponential increase in confirmed cases occurred during the periods of reduced pandemic fatigue. Many states announced a state of emergency to cope with the rebounding pandemic at those times. According to the protection motivation theory (Rogers & Prentice-Dunn, 1997), people may adjust their protective behavior based on risk appraisal. A recent study conducted in the US indicated that people tended to practice less social distance when the pandemic was mitigated in their local region (Pan et al., 2020). Furthermore, our model results confirmed the negative relationship between pandemic fatigue and confirmed case numbers

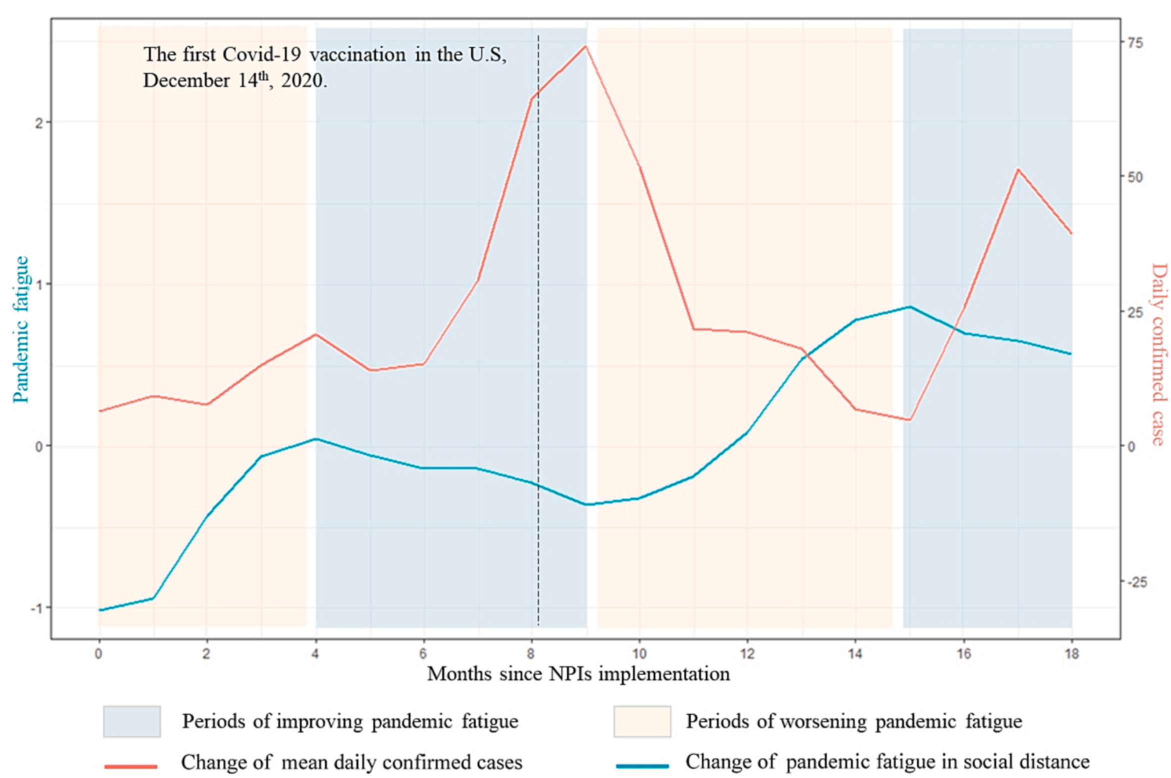

Fig. 7. Decreasing the COVID-19 cases, and increasing of pandemic fatigue levels. (The dotted line denotes the first COVID-19 vaccination in the US on December 14th, 2020 (BBC, 2020).)

(Table 2).

Notably, a sharp increase in pandemic fatigue levels occurred after the beginning of the vaccination program (from the 9th month to the 15th month), which was consistent with our initial hypothesis. Such increase of pandemic fatigue since January 2021 may be primarily due to the mental laxity caused by the large-scale vaccination program rollout. Several studies have confirmed that positive attitude to vaccination programs could lead to a lax adherence to social distance policies (Andersson et al., 2020). In addition, we observed a sharp decline in confirmed cases after January 2021 (Fig. 7), which may have triggered a reduction in risk perception and hence declining adherence to NPIs.

Second, we identified a significant moderation effect of the overall greenness on pandemic fatigue. After controlling for other factors, we found that people living in areas with high greenness experienced milder pandemic fatigue than those living in areas with low greenness. Thus, greenness could potentially facilitate adherence to NPIs. This finding is in line with a recent study conducted in Norway, which concluded that greenspace promoted social distance and indirectly mitigated the spread of COVID-19 (Venter et al., 2020). We propose two tentative explanations for this moderation effect (Fig. 8).

1) Enhancing mental health and self-discipline

Numerous studies have suggested that greenspace could significantly affect mental health by reducing mental fatigue, stress, and depression and enhancing positive emotions (Hartig et al., 2014; Kaplan, 2001; Richardson et al., 2013). When suffering from the negative emotions caused by long-term NPIs, people living in areas with more greenspace may recover faster from negative mental states than those living in areas with less greenspace. Hence, greenspaces could promote mental health, leading to better NPIs adherence.

Studies have also shown that people who have more exposure to nature perform better on tasks related to self-discipline than those deprived of nature (Berto, 2014; Taylor et al., 2002). Additionally, evidence suggests that greenspaces have other social benefits, including reducing impulsiveness and aggression and increasing social connections, which could enhance the sense of safety, cohesion, trust, and collaboration within communities (Holtan, Dieterlen, & Sullivan, 2014; Jiang, Mak, Larsen, & Zhong, 2017). These mechanisms can also explain the moderation effect of greenspaces on pandemic fatigue.

2) Facilitating active transport and physical activities

The pandemic has resulted in unprecedented changes in travel behaviors worldwide (Bhaduri, Manoj, Wadud, Goswami, & Choudhury, 2020). Evidence has shown that people tend to choose active transport (e.g., walking and cycling) or private cars rather than public transport since the pandemic began (Abdullah, Dias, Muley, & Shahin, 2020; Bhaduri et al., 2020; Shaer & Haghshenas, 2021). Greenspaces not only provide adequate space for people to maintain social distance but also promote active transport (Lu, Yang, Sun, & Gou, 2019; Sugiyama, Leslie, Giles-Corti, & Owen, 2008; Tilt, Unfried, & Roca, 2007; Wu, Lu, Lin, & Yang, 2019). One study confirmed that people visited parks more often during the pandemic than during the non-pandemic periods (Lu et al., 2021). People living in places with less greenspace may have more barriers to adjusting to the behavioral changes required by NPIs and thus find it more challenging to comply with them, leading to worsened pandemic fatigue.

Furthermore, greenspaces promote overall physical activity levels and physical health, which may further improve mental health and self-discipline. Available and accessible greenspaces offer opportunities for the public to engage in physical activities such as walking and cycling. Accumulating evidence shows that people living near greenspaces have higher physical activity and health levels (Akpinar, 2016; Kaczynski, Potwarka, Smale, & Havitz, 2009; Schipperijn, Bentsen, Troelsen, Toftager, & Stigsdotter, 2013; Yang, Lu, & Jiang, 2022). Sufficient physical activity contributes to physical health by reducing the risk of obesity and cardiovascular disease and improves mental health issues, such as stress, anxiety, and depression, thus promoting well-being (Barton & Pretty, 2010; de Wit et al., 2010; Hansmann, Hug, & Seeland, 2007; Harris, Cronkite, & Moos, 2006). People are more likely to maintain a positive emotional state and maintain self-discipline for NPIs behaviors. These potential positive effects of greenspace could help mitigate pandemic fatigue. In summary, this finding sheds new light on the cushioning effect of greenspace on pandemic fatigue during the COVID-19 pandemic.

Third, the urbanicity level significantly moderated pandemic fatigue. Compared with the most rural areas, urban areas experienced lower pandemic fatigue levels. This is consistent with the finding that people living in urban areas and metropolitan cities had better policy compliance and consequent intervention effectiveness than those living in rural areas (Credit, 2020; Liu, 2020; Tribby & Hartmann, 2021). The classification of urbanicity level in this study was mainly based on population, where the most urban category consisted of the “central” counties of large metropolitan areas with populations of more than one million. Therefore, to some extent, this index may be linked to urban density and governing capacity. In this context, we summarized two potential explanations for this finding (Fig. 8):

1) Risk perception and attitude to COVID-19

A previous US study investigated differences in COVID-19-related attitudes and risk perception across urban, rural, and suburban populations (Chauhan et al., 2021). The results revealed that people living in rural areas had lower risk perception and less concern about the pandemic than those living in urban areas. Similar patterns were also

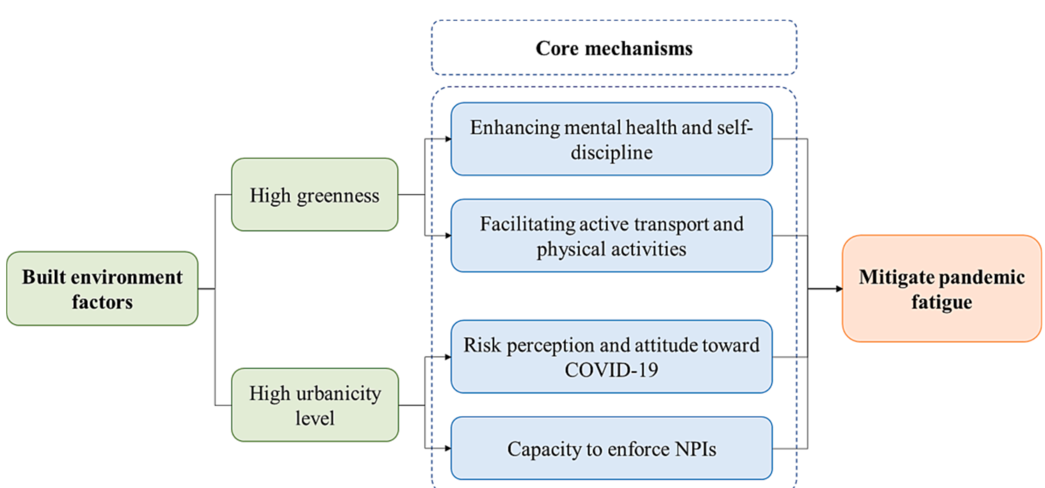

Fig. 8. Core mechanisms underlying the moderation effect of built environment factors on pandemic fatigue.

observed in other studies (Hamidi, Sabouri, & Ewing, 2020; Zhang et al., 2021). Hence, the higher risk perception of people living in dense urban areas may contribute to a more positive attitude toward NPIs, thereby moderating pandemic fatigue.

2) Capacity to enforce NPIs

Although the capacity to enforce NPIs by local governments is difficult to measure, it remains a non-negligible indicator that may affect the efficiency of NPIs. The social distance policies in more urbanized areas may be more strictly enforced to control the spread of COVID-19 (Ibrahim et al., 2020). In contrast, local governments in rural areas may have limited capacity or resources to enforce NPIs. Hence, the governmental capacity to enforce NPIs also affects public compliance with NPIs.

Implications

These findings have several implications for researchers and policymakers. First, dynamic changes in pandemic fatigue should be considered when assessing the effectiveness of NPIs, especially since the onset of vaccination programs, when sharp increases in pandemic fatigue were observed. Pandemics become hard to control if the public's pandemic fatigue and subsequent adherence to NPIs are not considered. Second, the impact of built environment factors (e.g., the NDVI and urbanicity level) on local NPIs efficiency should be considered. As our finding revealed, people living in areas with low greenness or low urbanicity levels may have more severe pandemic fatigue. Policymakers need to formulate appropriate policies to alleviate pandemic fatigue.

Limitations and future research opportunities

Our study has several limitations. First, the retail and recreation mobility data used in our study are a proxy for pandemic fatigue. Compared with survey data, mobility data cannot directly measure whether people adhere to some NPIs (e.g., if they wear a mask or attend large group gatherings). However, Google mobility data has been used in other studies to measure pandemic fatigue in social distance aspect, and the results were robust and consistent with the questionnaire results (Petherick et al., 2021). Second, NPIs enforcement strength was not considered in our model due to data unavailability. Even if the NPIs stringency is the same in two counties, different levels of enforcement may affect mobility behaviors. Third, both the mobility data and the control variables (e.g., demographics and socio-economic data) were at the county level rather than the individual level. Hence, the study is subject to ecological fallacy. Further studies with individual-level data are needed to address this limitation.

5. Conclusion

With prolonged enforcement of NPIs in many places worldwide, pandemic fatigue in social distance has received increasing attention from researchers and policymakers. This study investigated longitudinal trends in COVID-19 pandemic fatigue since the onset of NPIs implementation in the US. The results indicated that pandemic fatigue increased over time, with a sharp increase after large-scale vaccination programs began. In addition, we found that the NDVI and urbanicity levels significantly moderated the effect of NPIs on pandemic fatigue. People living in areas with high greenness and high urbanicity levels experienced relatively low pandemic fatigue than those living in areas with low greenness and low urbanicity levels. These findings shed new light on the effects of greenspace and urbanicity on pandemic fatigue during the COVID-19 pandemic.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104690.

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