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Insight into the nonlinear effect of COVID-19 on well-being in China: Commuting, a vital ingredient

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\begin{abstract}
\textbf{Background}: COVID-19 had a devastating impact on people’s work, travel, and well-being worldwide. As one of the first countries to be affected by the virus and develop relatively well-executed pandemic control, China has witnessed a significant shift in people’s well-being and habits, related to both commuting and social interaction. In this context, what factors and the extent to which they contribute to well-being are worth exploring.

\textbf{Methods}: Through a questionnaire survey within mainland China, 688 valid sheets were collected, capturing various aspects of individuals’ life, including travel, and social status. Focusing on commuting and other factors, a Gradient Boosting Decision Tree (GBDT) model was developed based on 300 sheets reporting working trips, to analyze the effects on well-being. Two indicators, i.e., the Relative Importance (RI) and Partial Dependency Plot (PDP), were used to quantify and visualize the effects of the explanatory factors and the synergy among them.

\textbf{Results}: Commuting characteristics are the most critical ingredients, followed by social interactions to explain subjective well-being. Commuting stress poses the most substantial effect. Less stressful commuting trips can solidly improve overall well-being. Better life satisfaction is linked with shorter confinement periods and increased restriction levels. Meanwhile, the switch from in-person to online social interactions had less impact on young people’s life satisfaction. Older people were unsatisfied with this change, which had a significant negative impact on their life satisfaction.

\textbf{Conclusions}: From the synergy of commuting stress and commuting time on well-being, the effect of commuting time on well-being is mediated by commuting stress in the case of China. Even if one is satisfied with online communication, the extent of enhancement on well-being is minimal, for it still cannot replace face-to-face interaction. The findings can be beneficial in improving the overall well-being of society during the pandemic and after the virus has been eradicated.
\end{abstract}

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1. Introduction

The COVID-19 pandemic shocked human society and had a devastating impact on our daily lives. Since the end of 2019, the novel coronavirus (i.e., SARS-CoV2) has continued to rage worldwide. It has caused more than 483 million infections and 6.13 million deaths worldwide as of March 2022, according to estimations by the World Health Organization (WHO). Despite large-scale vaccination and prevention measures in many countries, the virus continues to be disseminated and it mutates as it spreads. Amid the back-and-forth between loose and tight restrictions, it has been proven extremely difficult to end the global pandemic, and the potential exists for continued consequences. Since the very beginning of the outbreak, home quarantine and social distancing have been considered practical approaches to interrupting the spread of the virus. With the cancellation of flights and trains and limitations on the number of people carried by public transportation, there is likely to be an increase in travel modes such as driving because of enough space for distancing as the ensuing sense of safety (Shen et al., 2020). Many people adopt home offices to avoid going out, and the probability exists that such habit changes made due to this particular period would be maintained by many when the pandemic ends (Geng et al., 2020).

Contrary to many countries worldwide, China is still firmly implementing a national covid-zero policy. This strategy ensures that when a Chinese citizen tests positive for COVID-19 in a particular area, a few residential places like shopping malls and stations along their path are affected. These sites are evaluated into three ranks of the low, medium, and high-risk areas, and then different levels of control and quarantine policies are enforced. Also, green, yellow, and red health codes are adopted nationwide to demonstrate to individuals the different levels of risk for virus exposure, such as green for ordinary daily activities and yellow or red for quarantine, hospitalization, etc. (Meng et al., 2021) Abundant studies have been seen on the impact of the pandemic. However, fewer studies focused on cases like China, where the pandemic is tightly controlled, and most people have returned to their previous routines (Czerny et al., 2021). Further, preventing the virus from spreading has become a consensus and proactive approaches are taken in people’s daily lives (Li et al., 2021).

Wading in the sea of studies that focus on commuters, probing the effect of commuting behavior on well-being is gaining popularity rapidly (Martin et al., 2014; Chatterjee et al., 2020; Tian et al., 2020). Factors like living conditions, environmental issues, and workplaces all affect commuting behavior (Paleti et al., 2013; Gimenez-Nadal et al., 2018; Pawar et al., 2021). Building on that, aspects such as the distance and duration of commuting, the mode employed, and the social interaction are believed to be closely linked to well-being (Kroesen 2014, Rüger et al., 2017; Wu et al., 2019; Yin et al., 2021). In the era of the COVID-19 pandemic, health issues became vital, and many commuting trips were canceled or replaced by working from home (Xiao et al., 2021). Examining China provides a glimpse into how the aforementioned elements might influence people’s well-being when the epidemic has almost vanished and how it differs from the pre-epidemic period.

This study focuses on the shift in Chinese well-being from the pre-pandemic era to the pandemic period (July 2020). A questionnaire survey was conducted among residents from all provinces of mainland China, which provided reliable information on various aspects such as accurate personal and household attributes, travel characteristics, social interaction, and emotional attitudes. Based on data cleaning and pre-processing, a GBDT (Gradient Boosting Decision Tree) model, as a robust ensemble learning method, was developed to analyze the factors affecting well-being. Further, the non-linear relationships between the explanatory variables and the response variable were investigated. The findings can be beneficial in improving the overall well-being of society during the pandemic and after the virus has been eradicated.

2. Literature review

2.1. COVID-19 pandemic control strategies and their impact

On March 11, 2020, the WHO declared COVID-19 a global pandemic. Millions of people were infected with the virus in a relatively brief period (Gill et al., 2020). Many countries adopted various confinement measures nationwide or in several main cities to cope with the outbreak. According to a case study in China, controlling the routes linked to the epicenter at the beginning of the outbreak was an effective way to prevent COVID-19 from spreading (Lu et al., 2021). The cordon sanitaire in Wuhan bought an average 3-day delay of the viral spread to other cities (Kraemer et al., 2020). During the strictest period of lockdown in Germany, public transport lost its share of trips under drastic mobility restrictions while individual transport modes, particularly private cars, became increasingly used (Eisenmann et al., 2021). Using data from 1945 Indian participants during the pandemic, a one-year increment in commuters' age was found to be correlated with a 2% probability drop of going out due to health concerns (Pawar et al., 2021). Evidence from the UK pointed out that as the government announced stricter measures, a greater human-mobility reduction was observed and substantially reduced COVID-19-related deaths (Hadjidemetriou et al., 2020).

In Japan, self-restriction requests are not binding during the pandemic. A panel web-survey was conducted targeting residents in Kanto Region, including the Tokyo Metropolis Area. It found that risk perception, measured by COVID-19 dread, led to a higher likelihood of self-restriction of trips for eating out or leisure (Parady et al., 2020). Instead of a lockdown, Sweden’s strategy was primarily based on solid recommendations for society. A map-based survey to record people’s daily lives suggested that mobility, such as the possibility of telework, may exacerbate differences in different groups of people by gender, geography, or mobility (Bohman et al., 2021).

Among the various control strategies that have been implemented, restrictions on person-to-person contact and going out abound, impacting daily life, and how such changes related to well-being during the pandemic deserve further insight.
2.2. Characteristics influencing commuting

A multitude of characteristics can influence urban commuting behavior, including: demographic attributes (e.g., gender, age, education), socio-economic attributes (e.g., income, housing, car ownership), travel-related factors (e.g., commuting time, distance, mode), propensity factors (e.g., willingness to travel, purpose), and the built environment (e.g., transportation infrastructure, neighborhood environment, parking resources). The questionnaire design for this study drew many insights from these experiences (e.g., Paleti et al., 2013; Koslowsky and Krausz 1993, Wu et al., 2019).

The literature on commuting is extensive and numerous influences exist, of which a few examples are mentioned here. Strong commuting habits are generally unlikely to change even in significant disruption. However, the pandemic has been an extreme disruption. In studies prior to the pandemic, the willingness to change mattered most in the levels of commuting habit strength, suggesting transformations in behavior are related to contextual changes (Zarabi et al., 2019). Contextual change during the pandemic could be bound up with employment, the quality or availability of transport infrastructure, and available transport resources. For example, within the shifts in mobility habits among European commuters, the perception and preference for public transport innovations may bring about changes in mode choice (Tsafarakis et al., 2019). From the perspective of employment status, empirical findings based on the American time use survey demonstrated that employees spend more time commuting than the self-employed (Gimenez-Nadal et al., 2018). Supply variations in travel modes and resources also lead to commuting behavior changes. The expansion of the subway system in Beijing witnessed an apparent rise in the number of passengers and a drop in non-motorized and bus commuting trips (Wu and Hong 2017). For the shift in mobility habits among European commuters, the perception and preference for public transport innovations may bring about changes in mode choice (Tsafarakis et al., 2019).

During the pandemic, many people switched to home-based working, which brought about a reduction in commuting trips. Commuting by public transit was most strongly associated with this shift (Harris and Brannon-Calles 2021). COVID-19 mortality was linked with commuting mode choice in England, and spatial dependencies exhibited a stimulating effect (Francetic and Munford 2021). Transit riders were the most eager to return to their pre-pandemic commute, and male commuters showed a greater desire than females to reduce the impact of the pandemic on their journeys (Aoustin and Levinson 2021). As the epidemic subsided, many people returned to their workplaces and commuted. This process has not been richly explored in terms of changes in commuting and well-being and the factors that influence them.

2.3. Commuting and well-being

The relationship between commuting and well-being has been increasingly studied over the past decade often focusing on trip satisfaction. With the development of urbanization and transportation, job-housing imbalance in China has become more common, which means the distance and time of commuting have increased (Ministry of Housing and Urban-Rural Development of China and Baidu Map, 2020). The commuting problem squeezes out the time for leisure, adds to the economic burden and reduces the satisfaction and happiness of life. Also, commuting trips force travelers to make a lot of trade-offs (Lyons and Chatterjee 2008). Studies have found that the proximity of the workplace to the residence, which allows for non-motorized modes, will lead to happier commuting experiences (Wu et al., 2019; Yin et al., 2021). Moreover, commuters manifest more productivity in the workplace with a more positive mood, and active travel (walking and cycling) enhances this connection (Ma and Ye 2019). Based on 50 European cities, good practices in promoting active travel are proposed, such as temporary pop-up bicycle lanes and the expansion of pedestrianization with the speed limit of 30 km/h, where the pandemic has boosted more commuters switching to active mobility (Nalmpantis et al., 2021). In a pre-pandemic study in China, employer-provided shuttle bus commuters reported the highest level of travel satisfaction, followed by walkers and bicycle riders, probing how well-being varied across different modes. On the contrary, the poorest rating was received from regular city bus users. Meanwhile, commute frequency presented no conspicuous association with well-being (Zhu and Fan 2018). Car ownership was found to be another factor that was associated with well-being. It is revealed that greater satisfaction with commuting by car than by public transit, though car-driving commuters experience less joy and more stress, anxiety, and other negative moods (De Vos, Schwanen et al., 2013). Merely speaking individually, a private car may generate significant and positive relevance to people’s life satisfaction (Gan et al., 2019).

Researchers have also examined how travel might influence life satisfaction. A survey by the German Foreign Office suggested that commute stress plays a mediating role in the negative association between commute duration and life satisfaction. This role is more prominent among parents who are more profoundly influenced by reduced available time due to long commutes (Rüger et al., 2017). Another survey of commuters held in Sweden demonstrates that lower satisfaction with the commute is associated with decreased life happiness (Friman et al., 2017). Similarly, an indirect link between well-being and commute satisfaction was found through a survey in Oslo, Norway. Mainly via neighborhood and job satisfaction, commute satisfaction could be a reliable indicator of urban life eudaimonia (i.e., a well-lived urban life) (Mouratidis 2020). Furthermore, the subjective well-being of Dutch commuters showed a close connection to social contacts, and longer commutes were negatively associated with social contact satisfaction (Kroesen 2014). As such, evidence is building that how one commutes can affect one’s life satisfaction.

The emergence of the pandemic and fluctuations in the number of infections unlock novel dimensions to the study of commuting and well-being. Path analysis for England workers implicated that improving the public transit experience brought passengers joy along the route, reducing the negative association between commute satisfaction and leisure time happiness (Chatterjee et al., 2020). The ongoing pandemic has caused former commuters to reconsider present work arrangements, and fewer commuter trips may bring some improvement in well-being (Kun et al., 2020). Also, life satisfaction was found to increase for teleworkers if it replaced long commute trips in single-occupancy vehicles, but this was not found to be the case for long walking commutes (Shi et al., 2020).
In addition to the physical properties of commuting trips themselves, the evaluation indicators such as stress and satisfaction call for more in-depth exploration. Thus, this paper considers commuting as an entrance to examine the relationship between the COVID-19 pandemic and well-being as well as other associated factors.

3. Methodology

3.1. Survey design & data collection

To capture the Chinese well-being shift due to the COVID-19 pandemic, an online questionnaire consisting of 87 questions was distributed nationwide via social media (e.g., microblogs, WeChat, forums) from July 5th to 7th, 2020. More than five months had elapsed since the pinnacle of the epidemic, and only sporadic cases were reported from a few regions at that time. Data collection focused on provinces that had recently reported local infections but where the outbreak had diminished, control measures had been released.

At the recruitment stage, respondents were tested to have a good understanding of the survey topics. A representative sample was sought with gender parity and age groups representing the population. For age, the smallest group were people aged 60–69 (14%) and this was close to the percentage (18%) of people aged above 60 in the seventh census of China, 2020). Among the 800 responses collected, 688 sheets were valid for statistical analysis, 300 reported making work trips, with an average finish time of around 24 min. The distribution of respondents across the China mainland is presented in Fig. 1.

Principal subjects of the questionnaire included but were not limited to demographic and socio-economic characteristics (as summarized in Table 1), travel frequency, modes for commuting, life satisfaction, social interaction, and purposes of trips, both before and during the COVID-19 pandemic. Apart from some questions (e.g., confinement-related ones) that focused on respondents’ experiences at the peak of the epidemic, more were about what life was like at the survey time. Considering that the situation varies from town to town, the questionnaire data captured the living conditions of people both during and after the epidemic. Most of the features are quantified as percentages from 0 to 100, with 50 as neutral, to better capture the actual feelings of the respondents and to differentiate the degree of perception in greater detail, as well as to better cooperate with the data analysis process.

In the questionnaire, the concept of well-being was illustrated as “Well-being is a positive reflection of people who feel that their life is going well. Well-being generally includes a global judgment of life satisfaction as well as positive attitudes.” (Diener 2000; Veenhoven 2008, Weimann et al., 2015) For further insight, the word “well-being” was translated to “康乐感” in Chinese and was interpreted individually as “Perception or feeling of fulfillment and positive functioning, positive emotions and moods, satisfaction with life.” (Andrew and Withey 1976; Ryff and Keyes 1995) Answers were derived from the question “How is your well-being (e.g., fulfillment and positive functioning, positive emotions and moods, satisfaction with life) experienced during the COVID-19 pandemic?”, with a 0–100 scale. The single question approach follows similar approaches to measure life satisfaction in multiple social studies such as Lättman et al. (2019).

In the correlation test, connections were found between housing size, number of people living in the household, respondents’ well-
being, and frequency of travel, amongst others. For a household, bicycle and car ownership may affect members’ travel behavior and willingness to travel, as public transportation may not provide sufficient social distance among passengers.

Quarantine measures were employed to prevent the virus from spreading and the measures could be in place for quite a long time. For the peak period of the outbreak, multiple levels of local epidemic control measures were described in the questionnaire as unable to make all the travel (All unavailable), only essential trips for purchasing daily necessities (Only necessary trips), some of the trips are available with only a few retail shops open (Some trips available), most of the trips can be made with a few shops closed (Most trips available), no limitations or restrictions on travel (No limits). Respondents’ choices on these measures and their durations were listed in Fig. 2, reflecting that the severest period lasted about 2–3 months, and almost everyone’s travel was restricted.

Respondents chose their usual mode(s) of commuting before the epidemic and at the survey time. Fig. 3 compares the usage of different methods in both periods. People were able to choose multiple modes when answering this question. A considerable increase in the number of people working online can be seen. There is a significant increase of nearly 50% in the number of people commuting by car and an increase in walking and cycling but to a lesser extent. Fewer respondents reported using public transport, reflected in rail and bus. As the pandemic has continued, the commuting mode choice habits developed at this stage are likely to be maintained until the post-epidemic era.

Considering in-person interactions during the epidemic, Fig. 4 presents the respondents’ feedback about their social life. On a scale of 0–100, the distribution is indicated by the size and density of the shapes. There is a clear leftward shift, or decline, in the distribution of people’s social life satisfaction compared to the pre-epidemic period. The majority of respondents shared the view regarding online

![Fig. 2. Distribution of respondents based on the epidemic control measures and different duration levels. (wk = week, m = month).](image-url)
substitution for offline socializing during the epidemic. And such a substitution did not go as well as one might expect, with more respondents’ satisfaction gathered on the left side of 50.

3.2. Modeling approach

This research establishes a Gradient Boosting Decision Tree (GBDT) model to elaborate on the effect of epidemic control measures on commuting and well-being (Yin and Shao 2021). For its high prediction accuracy and ability to reveal non-linear relationships among variables, GBDT has been utilized in various kinds of tasks (Alballa and Al-Turaiki 2021).

The Gradient Boosting Regression algorithms were initially proposed by Friedman (2001). The GBDT approach generates a predetermined number of individual decision trees as a combination of gradient boosting and decision trees. Subsequently, each decision tree is separately trained, and their residual errors are calculated using a loss function. GBDT presents the final predicted value using the values indicated by each decision tree and their corresponding weights. In each iteration, weights are updated, and higher weights are assigned to decision trees with lower residual errors (Feurer et al., 2019). In this iterative process, residual errors of each stage are recorded, and GBDT aims to minimize them while selecting the set of decision trees for further research. Exploring the swiftest path in the gradient direction to the best result, GBDT integrates a series of weak (or simple) learners into a robust (or complex) model in a sequential procedure (Ye et al., 2009). In other words, the GBDT method creates an additive model in a forward stage-wise fashion, and the algorithms are presented below (Friedman 2001).

\[
F(x) = \sum_{t=1}^{T} f_t(x) = \sum_{t=1}^{T} \alpha_t h_t(x; w_t)
\]

\[
L(y, f(x)) = (y - f(x))^2
\]

Where \( f(x) \) is the approximation function of the response variable \( y; x \) represents a series of explanatory variables, such as demographic and commuting behavior characteristics in this research; \( h_t(x; w_t) \) is an individual decision tree, in which \( t \) is the number of the tree, \( T \) is the total number of trees applied in the model, and \( w_t \) is the parameter of the tree; \( \alpha_t \) means the weight of each tree, and a loss function \( L \) estimates it. The gradient boosting steps and algorithms can be summarized as follows, from which parameters are derived.
Input the training dataset \( T(x) = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)] \)

Initialize weak learner \( f_t(x) = \arg \min_{\alpha} \sum_{i=1}^{n} L(y_i, \alpha) \)

For \( t = 1, 2, \ldots, T \):

For samples \( i = 1, 2, \ldots, N \), calculate the negative gradient as

\[
y_{it} = \left[ \frac{\partial L(y_i, f(x_i))}{\partial f(x_i)} \right] f(x) = f_{t-1}(x)
\]

Based on the obtained errors used as the new actual values of the samples, a new tree \( h(x; w_t) \) is fitted.

Calculate the gradient descent step size \( \alpha_t = \arg \min_{\alpha} \sum_{i=1}^{n} L(y_i, f_{t-1}(x_i) + \alpha h_t(x_i; w_t)) \)

Update the strong learner \( f_t(x) = f_{t-1}(x) + \alpha_t h_t(x; w_t) \)

Output the final model \( F(x) = \sum_{t=1}^{T} f_t(x) \)

In this research, the GBDT model was established via Python’s scikit-learn package (Sklearn library). The optimization of the model involves the tuning of various parameters. Aiming to reduce the negative impact of overfitting, a regularization strategy that scales the contribution of each weak learner by a constant factor \( \omega \) named learning rate can be adopted:

\[
F_t(x) = F_{t-1}(x) + \omega h_t(x; w_t), \quad \omega \in (0, 1]
\]

Learning rate \( \omega \) scales the length of steps in the gradient descent’s optimization process. It shares a strong connection with the other parameter, the number of weak learners (i.e., the number of trees). Reducing the learning rate or increasing the number of weak learners by more than a threshold leads to overfitting. Moreover, considering an enormous value for learning rate or a small value for the number of estimators (i.e., the number of sub-learners) results in accuracy reduction (under-fitting). Therefore, optimizing these hyperparameters has been an immense concern. Following the decrease in the learning rate, more weak learners are required to maintain a constant training error. Thus, a trade-off between the learning rate and the number of weak learners is indispensable to achieve the best result. While controlling the number of weak learners, the complexity of a single tree (i.e., the number of nodes, defined by the parameter max depth) needs to be extended, ensuring that the model captures adequate relationships among variables (Wu et al., 2020). This study aims to increase the GBDT’s efficiency through tuning hyperparameters by combining the learning rate, number of weak learners, and tree complexity. The establishment procedure of the GBDT model is shown in Fig. 5.

### 3.3. Performance evaluation

In this research, the coefficient of determination (R-squared) is adopted to measure the performance of the regression model, and this performance indicator is illustrated below.

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{im} - y_{pn})^2}{\sum_{i=1}^{n} (y_{im} - y_m)^2}
\]

Where \( n \) is the number of data samples in the predicting dataset; for the response variable \( y \) of sample \( n, y_{an} \) represents the actual value, \( y_{pn} \) is the value predicted by constructed models; \( y_m \) represents the mean of the response variables’ values for all samples.

In the equation, the denominator is interpreted as the dispersion degree of samples, and the numerator is the error between predicted and actual values. The division of these two makes it possible to eliminate the impact caused by the dispersion in the data.

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Fig. 5. Visualized process of GBDT model establishment.
The value of R-squared ranges from 0 to 1, characterizing the explanation power of the model from weak to strong.

3.4. Analysis methods

GBDT models comprise a vast number of decision trees, which signifies that visual inspection methods of an individual decision tree are unable to be applied. Nevertheless, relative importance calculation can be implemented by answering two questions: which features are vital in computing the result? Moreover, to what level do they contribute to explaining the response variable (Ding et al., 2018)

Features are used by decision trees to split nodes in the feature selection process, the more frequently one is used in splitting, the more critical it is. The importance of a feature is then derived by averaging the result that each tree yields. This process is described schematically in the following equation.

\[
I(f) = \frac{1}{j} \sum_{i=1}^{j} \frac{1}{k} \sum_{j=1}^{k} \frac{n_f}{N} G
\]

Where \(I(f)\) means the importance of an individual feature; \(k\) equals the number of nodes, and \(j\) equals the number of trees; \(n_f\) represents the count of samples filtered out according to the feature at a single node; \(N\) is the number of samples; \(G\) indicates the Gini coefficient assigned to the feature at the node.

In general, importance values are scaled between 0 and 1 for more intuitive comparisons. Individual features often contribute differently to the results, but the relative importance sums up to 100%.

Another approach is the Partial Dependency Plot (PDP). It displays the dependence between the predicted outcome and a series of selected features, marginalizing other elements in the dataset. The partial function can be estimated using the algorithm below (Yang 2020).

\[
\tilde{f}_{xS}(x_S) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{j} \sum_{j=1}^{j} f(x_S, x_S^{(i)})
\]

This equation, based on the specific value of selected features \(x_S\), partial function \(\tilde{f}_{xS}\) outputs the average marginal effect of the

| Table 2 | Relative importance hierarchy of variables selected for the GBDT model. |
|---------|-------------------------------------------------------------|
| Variables | Importance (%) | Ranking |
| **Demographic & socio-economic attributes** | | |
| Age | 3.2 | 12 |
| Housing size | 1.3 | 16 |
| Do you have children (<18 years old) living with you | 1.1 | 17 |
| Car ownership | 0.9 | 19 |
| Bicycle ownership | 0.6 | 20 |
| **Sum** | 7.1 | |
| **Confinement measures** | | |
| How long did the restrictions last | 3.7 | 9 |
| The level of restriction measures | 3.5 | 10 |
| **Sum** | 7.2 | |
| **Commuting characteristics** | | |
| Feeling relaxed while commuting | 17.1 | 1 |
| Satisfaction of commuting trips | 13.4 | 2 |
| Feel safe using public transport | 11.7 | 3 |
| Ideal one-way commute time | 4.3 | 8 |
| Do you miss the commute you had before the pandemic | 3.4 | 11 |
| Do you usually use a bus pass | 2.1 | 14 |
| Feeling engaged while commuting | 1.7 | 15 |
| Travel frequency | 0.9 | 18 |
| Travel modes adopted | 0.4 | 21 |
| **Sum** | 55.0 | |
| **Social interaction** | | |
| Satisfaction with online interaction replacing the in-person one | 9.0 | 4 |
| Social life satisfaction before the pandemic | 7.7 | 5 |
| Approval of online interaction replacing the in-person one | 2.3 | 13 |
| **Sum** | 19.0 | |
| **Life attitude** | | |
| Overall life satisfaction before the pandemic | 7.0 | 6 |
| Would like to work/study at home when the pandemic ends | 4.7 | 7 |
| **Sum** | 11.7 | |
| **Total** | 100 | |
prediction. $x_i^0$ represents the actual values of unselected features, and $n$ is the number of samples in the dataset.

PDP expresses the model results as a function of the selected features. The method considers all instances and provides an overview of the global relationship between the explanatory and response variables.

Compared with conventional regression techniques, GBDT delivers higher prediction accuracy and can be applied to low-dimensional data. When handling non-linear relationships within the samples, GBDT exhibits a more pronounced advantage in not assuming relationships between variables beforehand. The relative importance charts enable a more intuitive hierarchy of explanatory capabilities, and partial dependence plots sketch non-linear curves directly. The weakness of GBDT approach is a lack of parallel data training due to dependencies among weak learners.

4. Results

Putting the concept of the previous section into practice, the GBDT model is built. Key parameters include the number of estimators, learning rate, max depth, subsample, and five-fold cross-validation to optimize the performance of GBDT and avoid overfitting. After five hundred times of fitting the data, the best results are obtained by setting the number of estimators (5000), learning rate (0.01), max depth (5), and subsample (0.8). The final model has an R-squared of 0.91. The relative importance of explanatory variables and partial dependency plots are generated and utilized for further analysis.

4.1. Relative importance results

The response variable is set as well-being during the pandemic. For GBDT modeling, during multiple rounds of fitting and optimization, myriad variables are extracted from the questionnaire. Nonetheless, quite a few contributed very little or even negatively to the fitting outcome. Therefore, only some of the explanatory variables are kept and categorized into five groups, demographic & socio-economic attributes, confinement measures, commuting characteristics, social interaction, and life attitude. Table 2 presents the relative importance hierarchy of variables.

Factors in the commuting characteristics account for the important explanatory powers, totaling 55%. The three most important variables for commuting were: feeling relaxed while commuting (17.1%), overall satisfaction with commuting (13.4%), and approval of the safety (in terms of protection against a viral infection) of using public transportation (11.7%). Since COVID-19 exposure poses a potential economic loss and health risk (including possible death), and commuting is an almost everyday routine, the perceived pressure from the infection risk and the agreement on “the risk of daily travel is under control” is tightly connected to well-being. In addition to these, the model also considers the ideal commute time based on usual travel modes, but the effect (4.3%) is not as

![Fig. 6. Partial dependence plots for variables ranked top in relative importance (dependent variable: well-being experienced during the COVID-19 pandemic).](image-url)
pronounced as for the factors mentioned above.

The social interaction and life attitude variables take the second and third places, contributing 19.0% and 11.7% to the results. During the epidemic, many tasks and communications converted to online forms, especially cross-provincial meetings, etc. Therefore, satisfaction with online interactions had a notable influence on people’s well-being, reaching 9%. The pre-epidemic lifestyle also plays a role in well-being, such as satisfaction with social interactions and living conditions, as the fifth and sixth most vital variables with 7.7% and 7.0% importance, respectively.

Since the COVID-19 virus had a little substantial impact on the daily lives of most Chinese people when the survey was conducted, the importance of confinement measures and their duration summed up to only 7.2%. Contrary to expectations, the 7.1% share implies that demographic and socio-economic attributes are far from a determining factor. The contribution of car, bicycle ownership, and travel modes adopted ranked at the bottom of all variables. This is perhaps in contrast to previous studies that found that users of single-occupancy or minority-occupancy transport modes do not strongly perceive the changes brought about by COVID-19 (Aoustin and Levinson 2021). At this point in China, many people may have rejoined public transport with proper personal protection.

4.2. Partial dependence plots

Partial dependence plots enable the presentation of non-linear relationships between the target variable and well-being. In this paper, the top six factors in the relative importance table are selected for illustration, mainly covering three categories: commuting travel characteristics, social interaction, and life attitude. From Fig. 6, as the axes extend, the relationship trend between each variable and well-being varied, with some producing strong fluctuations.

In response to the question, “How stressful is your commuting?” people rated their perceptions on a scale from “stressed, worried, hurried” to “relaxed, calm.” The variable was negatively correlated with well-being in the interval of 0–45, indicating that those stressed during their commute had lower life satisfaction. Conversely, following a rapid rise between 45 and 76, the curve passed 0.5 and remained largely at that level. It suggests that a trip does not need to be completely relaxing, but perhaps simply “relaxing enough” to increase life satisfaction.

The relationship between satisfaction with commuting trips and life satisfaction follows expectations with a roughly continuous upward trend as the score increases. When satisfaction reaches a certain threshold, such as around 75, the further increase in its value creates a limited contribution to the relationship, again suggesting that it is not necessary to have the absolute best commute but a sufficiently good one. It is worth noting that dissatisfied individuals with scores less than 20 contributed more significantly to the results than those who scored above 50. In other words, compared to the aforementioned stress variable, improving commuters’ satisfaction is more beneficial and pronounced for supporting life satisfaction.

Many respondents are likely believe that public transport is at high risk concerning COVID-19. The steep rise in non-linear results around 40 hints at the polarization of respondents’ attitudes. On one side, passengers who feel safe taking public transport had higher life satisfaction, though this trend plateaus after 70. In the interval between 45 and 65, feeling moderately safe using public transportation is still associated with a positive influence on life satisfaction. There is a steady decline in life satisfaction for those who do not feel safe using it.

As for the social interaction part, online interactions likely replaced many face-to-face interactions during the epidemic. Nearly all positive ratings (i.e., being satisfied with this change) had no influence. However, for those who were not happy, there was a slight linear decline until 20, when the decrease was much more robust. Remote communication, forced by social distancing and avoidance of mobility, heavily relies on the Internet and limits the types of activities available, which may cause a decline in satisfaction and a negative correlation with well-being. Then focusing on the undulation of the curve between 76 and 90, although people felt satisfied with this replacement, it may not be contributing to their well-being. Individuals who were not confident with their social interactions before the pandemic reported lower life satisfaction during the pandemic.

Low life satisfaction (below 40) before the epidemic is reflected in the persistent decline in well-being during the epidemic. Only individuals who had very high life satisfaction before (80 or above) positively influenced life satisfaction during the pandemic. Based on the values of the curves, the negative effect of low satisfaction is significantly more potent than the positive effect of the satisfying side.

4.3. The synergy between variables on well-being

In order to better visualize and analyze the interactions between the factors and their combined effects on the response variable, based on the hierarchy of relative importance and the correlations between variables derived from the descriptive analysis, two-way partial dependence plots are introduced in this paper.

Considering the combined effect of commuting stress and satisfaction on well-being, the most substantial positive impact on the outcome was found when relaxation reached over 65%, and satisfaction reached over 60% (see Fig. 7). When commuters are more stressed, the negative impact even given higher commute pleasure is more than the relief gained by reduced stress when they are
dissatisfied with commutes. Although enhancing both simultaneously is most effective in improving well-being, increasing satisfaction is more helpful when both scores are poor. Releasing the stress of social distancing and crowding during the epidemic is not noteworthy until satisfaction has reached “neutral.”

In Fig. 8, the commute time was measured by 0–180 min. As commuters report being more relaxed, its combined force with one-way travel time on well-being exhibits three phases. If people feel more stressed (scored less than 40 on the 0–100 scale) while commuting, shorter commute time (e.g., 20–40 min) exacerbates the negative effect on well-being, while a shift up to nearly no effect is detected when it goes beyond 120 min. This observation persists when the sensation of stress is less pronounced at approximately 40–60, but the correlation remains positive throughout. Studies have found that not all commuters develop adverse reactions to long-duration trips, but stress, especially if recurrent, is likely to arouse unpleasant feelings (Stokols et al., 1978; Schaeffer et al., 1988; Koslowsky and Krausz 1993, Olsson et al., 2013). Hence, respondents scoring 65 or more (i.e., more relaxed than stressed) show the highest positive effect on well-being when the one-way commute is less than 60 min, followed by the next peak when it is longer than 120 min. The canyon between 60 and 120 min might suggest that commuting at this intermediate duration stimulates respondents’ discomfort to some extent while not reaching the threshold of being prepared for a longer commute (He et al., 2016). The impact of commute time on attitudinal outcomes, like well-being, is mediated by stress during the trips.

![Fig. 7. Well-being on feeling relaxed and satisfied while commuting (both measured with a 0–100 scale).](image7)

![Fig. 8. Well-being on feeling relaxed while commuting (measured with a 0–100 scale) and ideal one-way commute time.](image8)
In Fig. 9, the synergy of restriction measures and their durations on well-being displays stable trends. First, shorter confinement periods are linked with better life satisfaction. However, as more trips became unavailable, participants’ reports differed. A peak is observed with “Level 5: no trips allowed at all” lasting for less than four weeks; the most stringent controls might have given individuals a stronger sense of safety and confidence to work together to win over the outbreak. In China, few places confronted COVID-19 without any limitations on daily life. It is reasonable that the virus spreading elsewhere and the flow of traveling people would still raise locals’ health concerns, which is reflected in depressed well-being. In addition, as the level of restrictions grew, individuals’ satisfaction improved. This result might suggest that people felt more content that the government had taken action.

Individuals were asked how satisfied they were with the switch from in-person to online social interactions. Respondents were required to measure their approval level from “Not at all” to “A lot,” using a 0–100 scale (see Fig. 10). When considering the contribution of age and this substitution on life satisfaction, it is easy to notice that young people aged 20–35 are less impacted by this moving online. When the approval level reaches higher than 30, a positive correlation with life satisfaction can be found for this age group. The same pattern still holds for 35-50-year-olds, but the strength of the correlation drops slightly. Among people over 50, the curve rarely remains positive, regardless of the approval level. Overall, though, any improvement was minor (<0.10). The lowest
negative correlation exists near the approval level of 50 and age over 65 years old, which can be interpreted as a lot of older people were not satisfied with this change. It had a significant negative impact on their life satisfaction. It would appear that their lack of in-person interaction with others during the outbreak resulted in remarkable negative effects.

5. Conclusion & discussion

This research is an effort to investigate how and to what extent people’s well-being was influenced during the COVID-19 pandemic and to explore the non-linear relationships between variables. China adhered to strict precautions and control measures throughout the period, which ensured the safety of citizens’ lives when the virus attacked. At the time this study was conducted (July 2020), people across China were still confronted with some local outbreaks, but more were settling back into their daily lives, which enables this study to build a foundation that informs changes in well-being and commuting behavior through the period to the post-pandemic era.

The nationwide questionnaire survey collected and reflected people’s personal and household attributes, living conditions, commuting behaviors, and social activities before and during the pandemic. In particular, the decrease in public transportation usage and the increase in non-motorized and car travel were validated by the data and coincide with many studies (Gkiotsalitis and Cats 2021, Przybylowski et al., 2021).

By establishing a GBDT model with well-being as the response variable, this study finds that commuting behavior factors are the most significant contributors. The less stressful and more satisfying commuting trips can provide a solid impetus to ameliorate well-being. However, it is not necessary to be perfect in both cases but to have a reasonably good condition. Meanwhile, reported by the respondents, stress comes from several aspects such as COVID-19, social activities, and traffic conditions, which play a significant mediating role in the effect of commuting time on well-being in this case. In China, despite the requirement to wear a mask, and scan or show the health code to ride, many passengers embrace public transportation again, which certainly requires sufficient approval of its safety (Dong et al., 2021) – it is also closely related to the dependent variable.

The digitalization of social interaction transcends the barriers of geographic separation, but it also deepens the gap between people of different ages, with varying levels of impact on well-being. Even if one is satisfied with online communication, the extent of enhancement in well-being is minimal, for it still cannot replace face-to-face interaction. Whereas the living patterns and feelings experienced prior to the outbreak maintain their momentum of effect on well-being during the pandemic. If you are fine with online social interactions, life satisfaction is likely to be sustained for a period. Still, it is not likely an excellent long-term approach as research on young people and online social interactions generally finds a negative relationship (Stiglic and Viner 2019).

Amid the lingering consequences of COVID-19, the results imply that enhancing health measures (e.g., improved cabin ventilation, more contactless facilities, and disinfection reinforcement) can be highly effective in alleviating commuting stress and advancing the well-being, especially for the efficient recovery of public transportation. Shorter-term but well-established policies could contribute to the well-being benefits. Older people are facing more challenges, where quarantine and remote communication constrain some of them to communicate mainly in person. In the widespread promotion of applications such as smartphone-dependent health certificates, more consideration needs to be paid to the variations in the adaptability of different population groups to achieve a more inclusive epidemic response policy.

Regarding the limitations of this paper, the sample needs to cover broader populations including those who may not be capable of completing the survey online. For groups that rarely use social media and other online platforms, the questionnaire may not be reachable, leaving them unrepresented. The analysis in this study was based on the commuting-related part of the obtained data, whereas the coverage for travel scenarios was limited. Finally, the interpretations and implications of the results are framed in terms of the specific policies and period of the study area.

The original survey was developed in Canada but did not have a national sample until the fall of 2020. Similarities and differences in the factors influencing civilian well-being across the two countries will be sought to identify common paths to enhance well-being. For the recording of commute frequency, time, and mode usage, adding Global Positioning System (GPS) records of travel trajectories or travel logs and mode identification will make obtaining more accurate trip patterns easier. Also, future research can be extended to a more detailed segmentation of the population based on demographic and socio-economic attributes, plus specific residential areas to study the impact of the COVID-19 pandemic on the well-being and travel behavior of different population groups.

Credit authorship statement

Yinan Dong: Conceptualization, Investigation, Methodology, Formal analysis, Writing - Original Draft. Yilin Sun: Investigation, Writing - Original Draft. E. Owen D. Waygood: Conceptualization, Investigation, Writing - Review & Editing. Bobin Wang: Investigation. Pei Huang: Investigation. Hamed Naseri: Writing - Review & Editing.

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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