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Xin Sun, Wei Song & Ye Wei

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Adapting Mobility: Insights from COVID-19 Impact on East Asian Regions

Abstract: The COVID-19 pandemic has profoundly transformed daily life and mobility behaviors, thereby creating an urgent need to understand these shifts. This study examines the spatial and temporal patterns of human mobility during the pandemic, with a focus on how these patterns vary across five East Asian countries and regions: Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China). By analysing Community Mobility Report and employing advanced analytical methods such as Gradient Boosting Machines and changepoints detection, the research identifies distinct adaptive behaviors in response to the pandemic. The findings reveal variations in the speed and nature of mobility adaptation across categories, such as retail, residential, and transit. While Mongolia exhibited relatively stable mobility patterns, Taiwan (China), Hong Kong, Republic of Korea, and Japan demonstrated notable adaptive responses. Furthermore, the study highlights the socioeconomic implications of mobility changes, providing insights into economic resilience and behavioral adaptation during health crises. These findings offer valuable evidence to inform public health strategies and economic recovery plans.

Keywords: Human mobility; Behavioral adaptation; COVID-19 Pandemic; East Asia; Economic forecasting

1 Introduction

The COVID-19 pandemic has triggered a global crisis of unparalleled scale, transforming societal norms and behaviours worldwide (Zabaniotou, 2020; Chen et al., 2024). Among the pandemic's most significant consequences has been its profound impact on human mobility patterns (Verschuur et al., 2021; Hu et al., 2022). Understanding these changes in human mobility is essential for evaluating the potential long-term effects on society, as insights into these mobility shifts are vital for public health planning, economic recovery, and strengthening resilience against future challenges.

To curb the spread of COVID-19, governments and individuals have faced the challenge of implementing and adapting to various containment strategies, including international travel restrictions, social and physical distancing, surveillance, and other preventive measures. These interventions, coupled with shifts in individual behavior, significantly altered physical mobility across urban and regional scales, impacting sectors such as transportation, tourism, labor markets, and commerce (Tirachini & Cats, 2020; Champlin et al., 2023; Hayakawa et al., 2023). Consequently, mobility data have become a vital resource for monitoring societal resilience and informing public health responses (Rowe et al., 2023; Sun et al., 2024).

In East Asia, the COVID-19 pandemic has triggered significant shifts in human mobility behavior. The region presents a compelling case study due to a confluence of unique characteristics that collectively shaped its distinct pandemic response and consequent mobility patterns. Culturally, prevalent collectivist norms fostered a high degree of societal acceptance and compliance with stringent public health measures such as mask mandates and mobility restrictions (Yang, 2024). Politically and institutionally, strong state capacity and centralized governance structures in key nations enabled the swift, top-down implementation of proactive containment policies. Technologically, advanced digital infrastructure and widespread mobile technology adoption facilitated the rapid deployment and public uptake of sophisticated digital contact tracing applications and real-time mobility monitoring systems, which were pivotal in balancing infection control with managed mobility. This unique interplay of cultural readiness, state capacity, and technological sophistication underpinned East Asia's generally proactive and resilient approach to the pandemic (Yeung, 2022; Haldane et al., 2021), fundamentally shaping the observed shifts in mobility behavior.

Despite extensive research on pandemic-induced mobility changes using mobile or public health data (Kan et al., 2021; Yu & Liu, 2023), critical gaps persist. First, most studies focus on national-level averages or single-city cases, overlooking subnational variations across diverse sociopolitical settings. Second, few integrate quantitative mobility metrics with behavioral adaptation theory to explain how and when populations adjust their movements. Third, mobility shifts and economic impacts are often analyzed in isolation, obscuring their interconnectedness. This gap is especially salient in East Asia, where varied governance models, compliance norms, and digital infrastructures likely drive heterogeneous adaptive outcomes, yet systematic cross-regional comparisons remain scarce.

To address these gaps, this study adopts a theory-driven approach, explicitly drawing on the cognitive, emotional, and behavioral adjustment dimensions of Behavioral Adaptation Theory to systematically explain the empirical differences in mobility behaviors across five East Asian societies: Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China). Firstly, regarding spatial patterns, it is essential to understand the variations in mobility behavior across six categories (retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential locations) and to identify how these behaviors differ among regions based on policy measures, cultural norms, and the severity of the pandemic. Secondly, concerning temporal patterns, it is important to analyze shifts over time, including critical "changepoints" that signify significant behavioral adaptations, such as the impacts of government restrictions or public health milestones. In this research, we construct the theoretical framework under the behavioral adaptation theory, and it seeks to address several key inquiries: (1) What are the tendencies and characteristics of human mobility behavior during the pandemic in Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China)? What similarities and differences exist among these countries and regions? (2) How can we quantitatively assess the overall responsiveness of human mobility data to the COVID-19 pandemic across these five countries and regions? (3) When did the human mobility behavior significantly change at various locations within the five countries and regions due to the epidemic? (4) Which category of mobility behavior affect the economic forecast results when the human behavior changes?

The remainder of this paper is organized as follows: Section 2 discusses the theoretical framework and literature review, focusing on the Behavioral Adaptation Theory and prior research on mobility behavior. Section 3 outlines the study area, datasets, and methodology. Section 4 presents the results, identifying trends, changepoints, and economic impacts of mobility behavior. Section 5 discusses the findings, contributions, limitations, and directions for future research. The final section provides general conclusions, emphasizing the importance of understanding mobility patterns during global health crises.

2 Literature Review and Theoretical Framework

2.1 Literature Review

Human mobility behavior, grounded in interdisciplinary theoretical frameworks such as spatial behavior theory, time geography, social network analysis, and complex systems theory, offers a critical perspective for examining contemporary societal challenges (Wang et al., 2020; Jin et al., 2024). This behavioral phenomenon exerts profound influences across multiple societal domains, including public health outcomes, urban spatial organization, transportation systems, community dynamics, and commercial activities (Huang et al., 2018; Long et al., 2015). Within the extensive corpus of human mobility research, investigations focusing on daily commuting patterns and routine travel behaviors have emerged as particularly salient areas of scholarly inquiry.

Prior to the pandemic, scholarly attention on human mobility centered on routine commuting and travel behaviors, highlighting its profound implications for social operation and economic development (Gu et al., 2023). Their work further unpacks the key drivers and spatiotemporal dynamics of intercity mobility, enriching the understanding of travel patterns beyond daily movements. However, the pandemic introduced unprecedented changes, such as widespread remote work and online education, which disrupted daily routines and increased screen time. Public transportation usage declined significantly, reflecting broader shifts in travel behavior (Rafiq et al., 2022; Fumagalli et al., 2021). Notably, recent research has further unpacked the stage-dependent spatiotemporal dynamics of pandemic-induced mobility changes. Gu et al. (2025) specifically examined how the COVID-19 pandemic and road infrastructure jointly exerted stage-dependent spatiotemporal influences on inter-city road travel in China, highlighting the heterogeneous impacts of the pandemic across different phases and geographic contexts. Therefore, it is evident that human mobility behavior changes markedly in response to the COVID-19 pandemic (Zhao et al., 2023). These transformations underscore the pandemic's profound influence on mobility, with drastic reductions in physical movement becoming a social norm.

In the context of COVID-19, mobility data has revealed critical trends and adaptation strategies, illustrating how individuals and communities respond to crises. Leveraging diverse data sources, researchers have employed a range of methodological approaches to dissect these changes. Key among these are sophisticated temporal analysis techniques. For instance, numerous studies have employed simulation and predictive models to forecast the potential dissemination of the novel coronavirus (Zheng et al., 2021; Hu et al., 2021). Time series decomposition has helped isolate underlying trends from seasonal patterns and noise, revealing the pandemic's long-term impact on movement (Doornik et al., 2021; Zbezhkhovska & Chumachenko, 2025). Machine learning models have been applied to forecast mobility trends or identify distinct behavioral archetypes emerging during the crisis. By combining these datasets with analytical tools like those mentioned above, researchers have been able to uncover significant shifts in behavior and their implications for public health and economic resilience (Pavlović et al., 2022; Cao & Liu, 2024). Additionally, studies by Bonaccorsi et al. (2020) on pandemic impacts and Okamoto (2022) exemplify the connection between mobility patterns and economic outcomes, further validating this critical relationship. Numerous studies have analyzed pandemic-induced mobility changes, typically using mobile device data or public health datasets (Kan et al., 2021; Yu & Liu, 2023). However, most of these studies focus on national-level averages or city-specific cases and tend to treat mobility and economic effects separately. Furthermore, spatial analysis has played a vital role. Studies have utilized techniques such as spatial autocorrelation measures to identify clusters of high or low mobility reduction and their spatial persistence (Hajlasz & Pei, 2024; Chapin & Roy, 2021). Geographically Weighted Regression (GWR) and other spatial regression models have been employed to explore how the relationship between mobility changes and potential drivers varies across space (Chen et al., 2021). Based on previous research, what remains underexplored is how changes in mobility behavior across different sociopolitical and cultural contexts translate into adaptive outcomes. Moreover, few studies systematically integrate behavioral adaptation theory with quantitative mobility metrics to understand both the temporal dynamics of behavioral change and its economic consequences. This gap is especially pertinent in East Asia, a region marked by diverse governmental responses, public compliance norms, and digital infrastructure.

This gap in the literature highlights the need for a unifying theoretical lens, one capable of contextualizing empirical observations of mobility shifts within a coherent framework of human decision-making and behavioral adjustment. While reviewed studies document the what and where of mobility change, they rarely ground these observations in a theory explaining the how and why of individual and collective adaptation processes. Such a foundation is essential for linking observed spatiotemporal mobility patterns with the underlying cognitive and social mechanisms underpinning them, and ultimately for unpacking their socioeconomic ramifications. This need thus frames the introduction of Behavioral Adaptation Theory as a scaffold linking empirical measurement with conceptual elaboration.

2.2 Theoretical Framework

Behavioral Adaptation Theory explores how individuals adjust their behavior in response to environmental perturbations to enhance survival and well-being (Hamilton et al., 2018; Yu et al., 2023). Grounded in the research (Osman, 2010; Rachman, 2025), this theory posits that humans continuously interact with their environment through cognitive processing and behavioral feedback loops, forming adaptive cycles that optimize outcomes under constraints. Mobility behavior, as a critical manifestation of human adaptation, is inherently non-static; it evolves through interactions with physical landscapes, social norms, and cultural infrastructures (Golledge, 1997; Xu et al., 2025). The COVID-19 pandemic presented a massive, shared environmental perturbation, yet the adaptive response in mobility was filtered through region-specific contexts. Behavioral Adaptation Theory provides the lens to understand this filtering process. It suggests that the observed empirical differences across regions are not random but rooted in varying expressions of these core adaptation dimensions, shaped by local factors. Individuals develop various strategies and mechanisms to cope with environmental changes, including changing habits, or altering social behaviors. As depicted in Fig.1, our study applies this framework to human mobility-spatial environment dynamics during the COVID-19 pandemic. This application directly addresses the gap identified in the literature review. While prior research has meticulously documented pandemic-induced mobility changes using diverse data and methods, Behavioral Adaptation Theory provides the explanatory mechanism to synthesize these findings. It frames the observed reductions in public transport use, the emergence of new travel archetypes, and the spatiotemporal heterogeneity not merely as statistical patterns, but as the aggregate outcome of countless individuals undergoing cognitive and behavioral adaptation cycles in response to risk and policy cues. The theory illuminates how individuals utilize cognitive maps and risk-based decision-making to reconfigure mobility in novel social contexts (Sih et al., 2011). However, rising awareness of pandemic severity triggered spatial cognition shifts, altering environmental perceptions and navigation priorities (Vanhove et al., 2021). For instance, real-time infection data amplified perceived vulnerability in crowded spaces, prompting preemptive avoidance even before policy mandates (Pullano et al., 2020). During the pandemic, people adjusted their geographical decisions, such as deciding whether to go out, where to go, and when to engage in these activities. Consequently, spatial interactions became subject to COVID-19 constraints. The intensity of these interactions was influenced by policies and public health measures. Over time, the pandemic's impact on human mobility patterns became increasingly evident, with distinct trends emerging across different countries and regions. These variations were shaped by both individual choices and governmental interventions (Kraemer et al., 2020). Building on this theoretical scaffold, the empirical approaches reviewed earlier, including time series decomposition to isolate trends, changepoint detection to identify behavioral shifts, and spatial regression to model geographic variation, are thus reconceptualized within this framework as tools for quantifying different phases and manifestations of the adaptation process. They move from descriptive analytics to the measurement of a theoretical construct.

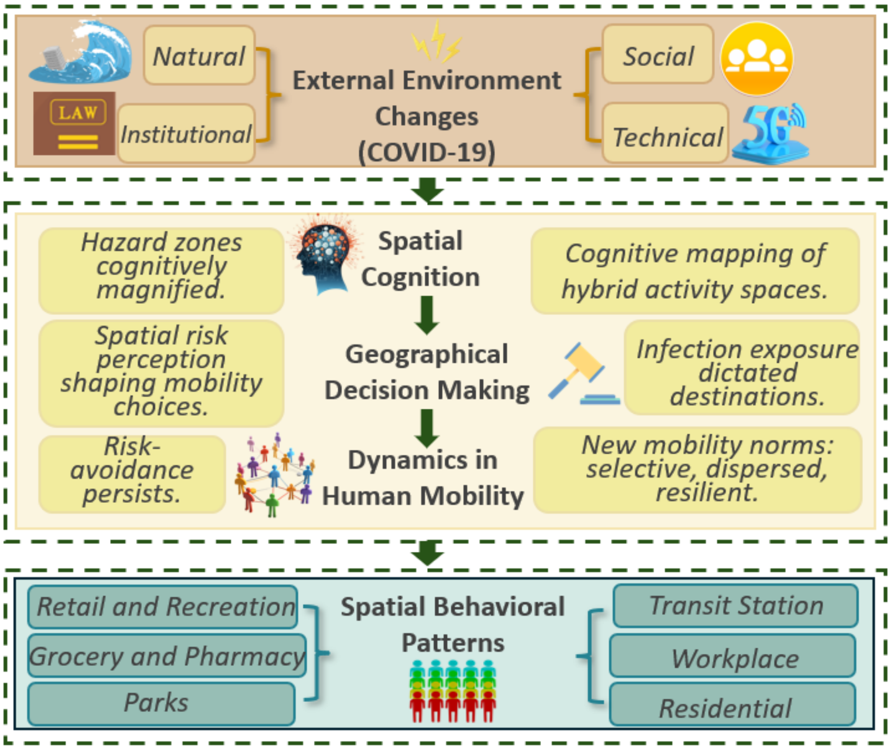

Fig.1 Analytical framework of human mobility behavior under the COVID-19 pandemic

Guided by this framework, our study moves from description to theory-informed explanation. This allows us to interpret the empirical results not just as divergent trends, but as manifestations of distinct adaptive pathways. In this research, we construct the theoretical framework under the behavioral adaptation theory. To bridge the theoretical framework and the empirical tools, we conceptualize the Responsive Index (RI) as a quantitative expression of behavioral adaptation. Specifically, RI measures the degree to which individuals reduce or increase mobility in response to perceived risk and policy constraints. These factors are key indicators of adaptive decision-making, which is shaped by both individual assessments and external mandates. Similarly, changepoint detection identifies temporal thresholds in behavior, representing critical moments when individuals re-evaluate risk or when external interventions prompt shifts in behavior. These empirical measures align with Behavioral Adaptation Theory by operationalizing behavioral change as a response to evolving environmental cues and social norms during the pandemic. This allows us to systematically test the theory's propositions against observed mobility data, thereby addressing the literature's shortcoming in theoretically integrated quantitative analysis. Critically, this framework acknowledges the complex interplay and potential difficulty in fully disentangling the individual effects of perceived risk and policy constraints on mobility, especially as adaptations evolve over time.

3 Materials and Methods

3.1 Study area and data

3.1.1 Study area.

As illustrated in Fig.2, this study focuses on five East Asian regions: Mongolia, Japan, Republic of Korea, Hong Kong (China), and Taiwan (China). This selection provides a strategic cross-section of the region, capturing a diverse spectrum of pandemic containment strategies, economic development levels, and cultural contexts. A key practical consideration enabling a standardized comparative analysis was the consistent public availability of Google's Community Mobility Reports for these jurisdictions throughout the study period, which serves as the core dataset for this research. China and the Democratic People's Republic of Korea are not included in the comparative framework as comparable mobility data were not published. By examining this strategically chosen and analytically viable set of societies, the research aims to derive insights that can inform future public health responses in similar sociocultural and technological settings globally.

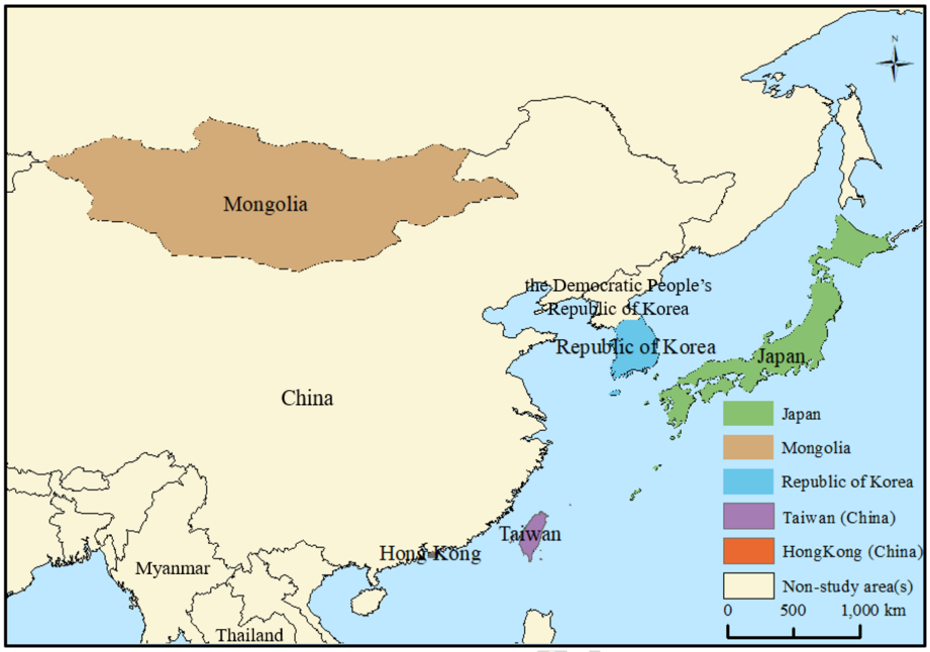

Fig.2 The study area of five countries and regions in East Asia, including Mongolia, Japan, Republic of Korea, Hong Kong (China) and Taiwan (China)

3.1.2 Data

This study establishes a consistent observation period from February 15, 2020, to October 14, 2022 (139 weeks), applied uniformly across all datasets. Data encompasses Google's Community Mobility Report, COVID-19 case counts, and economic indicators collected concurrently across five countries and regions throughout this period, ensuring full temporal alignment for integrated analysis.

(1)Human mobility data.

Google's Community Mobility Report (CMR) compiles daily mobility data for five East Asian countries and regions-Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China)-using anonymized location history data from individuals using Google apps on smartphones or handheld devices (Aktay et al., 2020). The dataset tracks variations in mobility across six categories: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential locations, as compared to a baseline (Table 1). For the residential category, the data reflect changes in the length of stay, while

the other five categories capture changes in the number of visits. The Google Mobility Report baseline, defined as the median value from January 3 to February 6, 2020, is set by Google and used globally to enable comparative tracking. Mobility scores represent percentage changes from this baseline, with scores below zero indicating decreases and scores above zero indicating increases. While this data may underestimate the true magnitude of pandemic-induced mobility shifts in certain regions, the Google baseline nevertheless serves as a valuable reference point for calculating relative percentage changes. To minimize distortion and improve interpretability, all daily mobility data were aggregated into weekly averages, smoothing out day-of-week effects and irregularities.

Table 1. The explanation of six different place categories on human mobility behavior.

Location categories	Subclassification
Retail and recreation	Restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
Grocery and pharmacy	Grocery markets, food warehouses, farmers markets, food shops, drug stores, and pharmacies.
Parks	Local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.
Transit stations	Public transport hubs such as subway, bus, and train stations.
Workplaces	Places where people engage in professional activities or work.
Residential	Housing and living accommodations, such as houses, apartments, condos and others.

(2) Cases of COVID-19 pandemic and economic indicators.

Data on daily new confirmed cases of COVID-19 were obtained from the Johns Hopkins Coronavirus Resource Center. To align with the mobility data, daily case counts were aggregated into weekly averages. The study period spans from February 15, 2020, to October 14, 2022, covering a total of 139 weeks. In addition, economic indicators, including GDP, GDP growth rates, and unemployment rates for Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China), were collected from the World Bank and the International Monetary Fund at their native annual frequency. This difference in temporal analytical units is a critical methodological consideration: (1) Granularity & Dynamic Response: Weekly mobility and case data capture short-term behavioral and epidemiological shifts, while annual economic indicators reflect aggregate long-term trends. Consequently, our model inherently analyzes cumulative economic impacts observable at yearly level resulting from weekly pandemic dynamics; (2) Temporal Misalignment & Attribution: The annual resolution of economic data limits precise attribution of impacts to specific weekly events. Statistical techniques mitigate but cannot fully resolve this fundamental scale discrepancy; (3) Data Availability Constraint: Annual reporting is the standard for key macroeconomic indicators across international databases. Higher-frequency proxies were infeasible given the study's comprehensive indicators and cross-country scope. Thus, economic indicators retain annual resolution in our primary models. These data provide essential context for evaluating socioeconomic implications of mobility changes during the pandemic, enabling robust assessment of medium-to-long term relationships between pandemic dynamics, policy stringency, and economic outcomes.

3.2 Methods

3.2.1 Gradient Boosting Machine (GBM)

The Gradient Boosting Machine (GBM) method, introduced by Friedman (2001), is an ensemble learning technique that iteratively combines weak learners to enhance predictive accuracy and robustness. In this time-series supervised learning framework, we treated each country/region as an independent case study. For each geographical unit, we constructed a longitudinal dataset where every observation represents a weekly time unit across the full study period (139 weeks total). The model was specifically applied to evaluate how mobility behavior impacts economic forecasting. In the context of this paper, economic forecasting is explicitly defined as the use of aggregated mobility behavior to predict near-term changes in economic indicators. The dataset was rigorously split into training (1~111 weeks, 80%) and testing subsets (112~139 weeks, 20%), preserving temporal sequence integrity by using earliest data for training and most recent for validation.

There is a training dataset$\{(x_i, y_i)\}_{i=1}^{N}$, where x_i represents the features and y_i represents the target variables. Mobility data were employed as input variables, with economic indicators serving as target variables. The goal of GBM is to build a final model $F_M(x)$ by combing a series of weak learners $h_m(x)$ (Friedman, 2001):

$$F_M(x) = \sum_{m=1}^{M} \gamma_m \, h_m(x) \tag{1}$$

Where γ_m is the weight for each learner, typically determined by minimizing the loss function. In each iteration, GBM updates the model through the following steps:

(a) Initialize the model $F_0(x)$:

$$F_0(x) = arg\ min_\gamma \sum_{i=1}^{N} L(y_i, \gamma) \tag{2}$$

(b) For each internation, $m = 1, 2, \dots, M$, compute the residuals r_{im}:

$$r_{im} = -\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} |_{F(x)=F_{m-1(x)}} \tag{3}$$

Train a weak learner $h_m(x)$ to fit the residuals r_{im}, and update the model:

$$F_M(x) = F_{m-1(x)} + \gamma_m h_m(x) \tag{4}$$

A key innovation in GBM model is the incorporation of lagged mobility features, which reflect the real-world delay between behavior and economic response. Specifically, we generated lagged versions of each mobility category for multiple time windows. These lagged features were constructed by shifting the time series of the mobility index backward.

3.2.2 Responsive Index (RI)

Responsive index (RI) was employed to quantify the degree of responsiveness in human mobility behaviors to the COVID-19 pandemic (Huang et al., 2021). A decrease in mobility within categories such as retail and recreation, grocery and pharmacy, parks, transit stations, and workplaces is considered a positive response, while an increase is regarded as a negative response. For the residential category, the index is interpreted inversely, whereby an increase in residential mobility indicates a positive response and reflects compliance with stay-at-home measures. With the reference of research (Huang et al., 2021), the formulas are as follows:

$$R_A = \frac{\sum_i S^i_{A_\propto}}{\sum_i S^i_{A_\propto} + S_{A_\beta}} \tag{5}$$

$$R_B = \frac{\sum_i S^i_{B_\propto}}{\sum_i S^i_{B_\propto} + S_{B_\beta}} \tag{6}$$

$$RI = R_A - R_B \tag{7}$$

The smoothed curve of changes in human mobility behavior will intertwine with the baseline, which has a value of 0%. The calculation of the RI is divided into two parts: the first part, R_A, represents the ratio of the area below the baseline (S_{A_α}) to the total area from -100% to 0% and R_A quantifies the strength of the positive response. As for the second part, R_B, represents the ratio of the area above the baseline (S_{B_α}) to the total area from 0% to +100% and R_B quantifies the strength of the negative response. The area between the baseline and the smoothed time series is denoted as α while the space outside of α is denoted as β.

The responsiveness index (RI) ranges from -100% to +100%, where an RI of 1 indicates perfect responsiveness hypothetically. A positive RI signifies a cumulative positive response within a defined period, whereas a negative RI indicates the opposite.

*3.2.3 The quantification of Changepoint*s

Changepoints indicate moments when mobility patterns deviated substantially from previous trends, often corresponding to critical events such as the implementation of lockdowns or the relaxation of restrictions. This study employs the Changepoint framework (Killick & Eckley, 2014; Hasselwander et al., 2021), which uses statistical methods to segment time series data into distinct phases. Changepoints were detected with 95% confidence intervals (Hinkley, 1970), highlighting key transitions in mobility behaviors (Hasselwander et al., 2021). This analysis provides insights into the timing and magnitude of population level adaptations to the pandemic across Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China).

Suppose we have a time series dataset $Y = (y_{1,} y_{2,} \dots y_T)$, and we suspect that there are multiple structural changepoints in the data, which divide the time series into several segments. Our goal is to identify the number of changepoints and their locations. Assume that there are m changepoints in the time series, located at $\tau_1, \tau_{2,\dots} \tau_m$, dividing the time series into $m + 1$ segments. The observations in each segment can be considered to come from different statistical models. A standard assumption is that observations within each segment follow the same probability distribution, though with segment-specific parameters. For instance, it is common to assume that within each segment, the observations y_t follow a normal distribution with distinct means and variances.

If τ_i denotes the i-th changepoint, with $\tau_0 = 1$ and $\tau_{m+1} = T$ (the start and end points of the time series), the model for each segment is as follows:

$$y_t \sim N(\mu_i, \sigma_i^2), \text{ for } t \in (\tau_{i-1}, \tau_i], i = 1, 2, \dots, m + 1 \quad (8)$$

where μ_i and σ_i^2 represent the mean and variance of the time series in the i-th segment.

As shown in Fig.3, this diagram presents a comprehensive workflow framework investigating the relationships between human mobility patterns, the COVID-19 pandemic, and economic performance. The process begins by integrating Input Data from three critical sources. This foundational data feeds into a suite of advanced Methods including the Responsive Index to quantify behavioral reactions, Changepoints Detection to identify significant temporal shifts in trends and GBM Modeling to build predictive models capturing complex interactions. The analysis unfolds sequentially across four questions, as stated in Introduction. This progression signifies an evolution in the research focus: starting with immediate empirical analysis and practical interpretations of behavior and regional disparities, moving through concrete economic predictions, and ultimately culminating in the development of broader theoretical understanding.

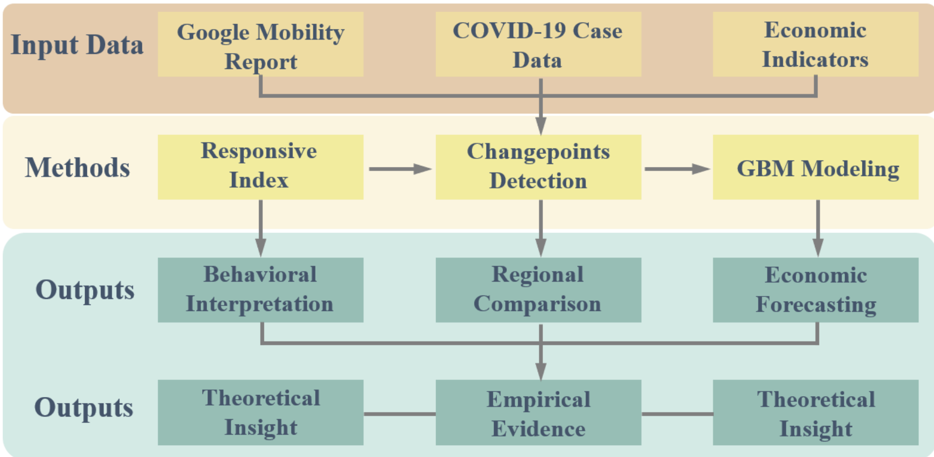

Fig.3 Workflow diagram for quantifying regional adaptation to COVID-19

4 Results

4.1 The tendency in human mobility behavior and confirmed cases

As shown in Fig.4, the five East Asian countries and regions, namely Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China), displayed distinct human mobility patterns and COVID-19 case trajectories during the pandemic. Each location experienced significant relative shifts in mobility behavior. Table 2 outlines the diverse containment policies adopted in these areas.

Table 2. Various restricting measures of human mobility during the pandemic in five East Asian countries and regions.

Countries and regions	Restricting Measures
Mongolia	Closure of international borders;
	Suspension of international flights;

	Quarantine measures for incoming travelers;
	Localized lockdowns in affected areas;
	Travel restrictions within the country.
Japan	Entry bans for travelers from certain countries; Quarantine requirements for incoming travelers;
	Suspension of visa issuance for certain countries;
	Advisory against non-essential domestic and international travel;
	Limitations on public transportation services.
Republic of Korea	Mandatory quarantine for incoming travelers;
	Entry bans for travelers from high-risk countries;
	Restrictions on visa issuance;
	Social distancing measures, including limitations on gatherings;
	Suspension of certain types of visas.
Hong Kong	Entry restrictions and quarantine measures for incoming travelers;
	Suspension of visa-free access for certain nationalities;
	Closure of certain border checkpoints;
	Mandatory testing and quarantine for individuals with potential exposure;
	Restrictions on public gatherings and social activities.
Taiwan (China)	Strict border controls and quarantine measures for incoming travelers;
	Entry bans for certain nationalities;
	Mandatory mask-wearing in public places;
	Social distancing measures in public spaces;
	Restrictions on large gatherings and events.

The first type, exemplified by Mongolia, represents a pattern of Minimal Adaptive Adjustment. This was characterized by consistent growth in mobility across all six categories during the study period. Despite pandemic conditions, mobility levels in Mongolia generally remained above baseline, with grocery and pharmacy visits showing particular resilience. This stability can be explained by a specific adaptive pathway in which stringent national border closures created a strong cognitive appraisal of a protected domestic environment, leading to relatively low perceived internal risk. Consequently, mobility patterns showed remarkable consistency, with no substantial declines observed. However, workplace mobility exhibited a temporary reduction during two infection waves (August 2021-February 2022), indicating pandemic-induced behavioral adjustments. The overall mobility resilience reflects an adaptation strategy centered on maintaining near-normalcy under conditions of externally containment. The second type, represented by Republic of Korea and Hong Kong, demonstrates a pattern of Dynamic and Responsive Adaptation. This was characterized by noticeable, policy-sensitive fluctuations in mobility. For instance, Republic of Korea saw increased park visits (a compensatory strategy) alongside decreased transit and workplace mobility. Hong Kong exhibited sharp declines in most non-essential categories during outbreak peaks. This pattern aligns with an adaptation process driven by strong cognitive appraisal of rapidly changing local transmission risks. The observable fluctuations are the direct outcome of repeated cycles of behavioral adjustment, which involve tightening and relaxing movements in close response to epidemiological and policy cues. The third type, represented by Japan and Taiwan (China), illustrates a pattern of Sustained Precautionary Adaptation. This was characterized by consistent decreases in mobility across most categories, with levels generally below baseline throughout the observation period. In Japan, transit station and workplace mobility experienced pronounced declines, and these patterns persisted without recovering to pre-pandemic levels by the end of the observation period. Residential activity consistently exceeded the baseline, reflecting prolonged adherence to stay-at-home measures. Similarly, Taiwan (China) saw marked declines in retail/recreation, park visitation, and transit station usage, with particularly sharp drops in June 2021 and June 2022. This pattern suggests a dominant adaptation pathway where a consistently high cognitive appraisal of risk, potentially reinforced by prevailing social norms and prolonged advisory measures.

Despite regional differences, a common trend emerged across all five regions: increased residential mobility during peaks in confirmed cases. This universal response underscores a core principle of Behavioral Adaptation

Theory: when faced with a salient and severe threat, the most immediate and convergent behavioral adjustment is retreat to the perceived safety of home (Bamney et al., 2023). Similarly, the general increase in grocery and pharmacy visits reflects an adjustment prioritizing essential needs, a basic adaptive strategy under constraint (Zheng et al., 2025). Notably, February 2022 saw a significant case peak across all regions, coinciding with sharp, synchronized behavioral shifts. This event acted as a powerful external shock, temporarily aligning the cognitive appraisal of risk across diverse contexts, leading to a convergent, though temporary, peak in behavioral adjustment. During the major case surge in early 2022, all regions showed synchronized behavioral shifts: residential mobility increased significantly while transit usage declined sharply. Notably, by October 2022, divergent policies drove distinct mobility trajectories. Mongolia maintained strict controls, preserving stable mobility patterns, whereas Hong Kong's relaxation led to retail mobility recovery despite localized restrictions. Policy adjustments over time further shaped mobility evolution: Japan's prolonged travel advisories sustained reduced workplace activity; Japan's prolonged reductions, Republic of Korea's delayed park recovery, and Taiwan (China)'s dual declines all exemplify how region-specific interactions between policy, social norms, and individual adaptation processes generated the distinct, empirically observed mobility trajectories. This integrated perspective, which combines spatial and temporal dimensions, illustrates how region-specific policies, including both sustained restrictions and gradual reopening, generated divergent mobility outcomes even within the same phase of the pandemic, thereby offering a more refined understanding of behavioral adaptation.

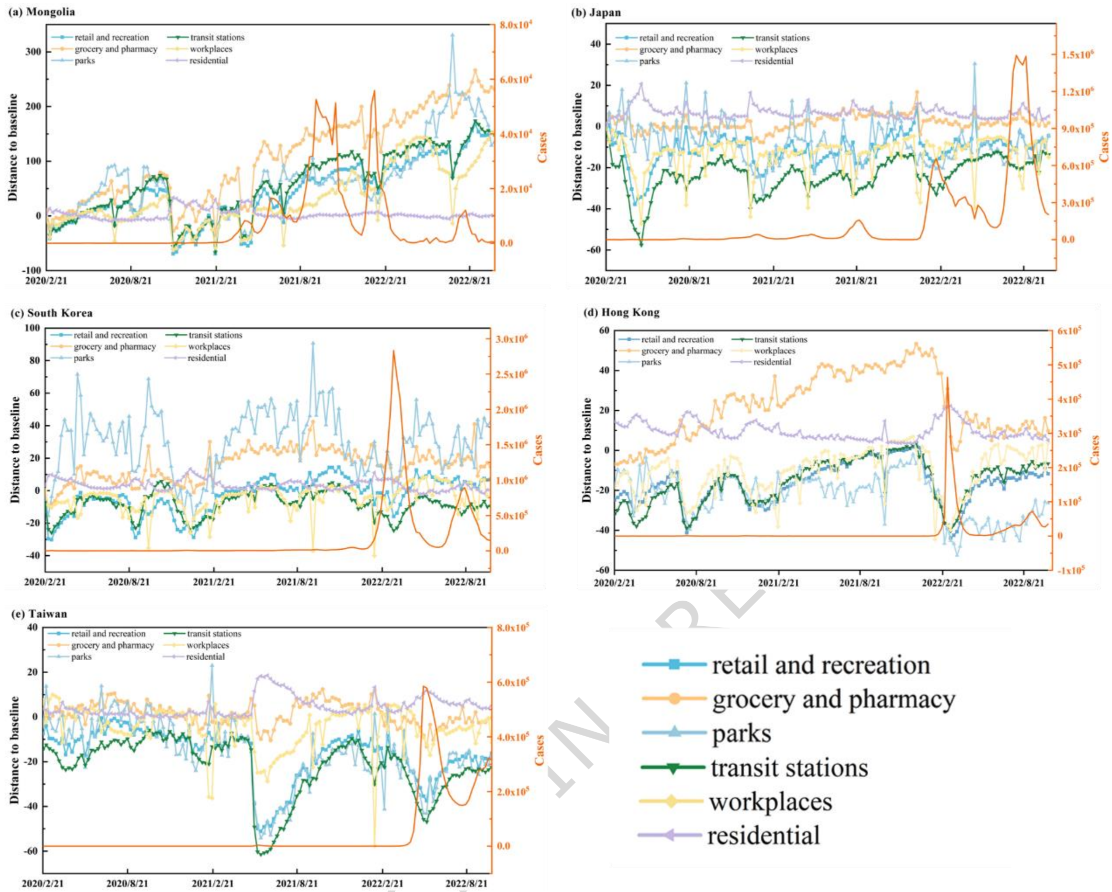

Fig.4 Pattern of Google location and cases in five countries and regions from February 15th, 2020, to October 14th, 2022. (a) Mongolia; (b) Japan; (c) Republic of Korea; (d) Hong Kong; (e) Taiwan (China)

In the later stages of the pandemic, mobility patterns began to recover compared to the early stages, particularly in Mongolia. However, in Republic of Korea, Japan, Hong Kong, and Taiwan (China), mobility levels across most categories did not return to pre-pandemic norms. This phenomenon reflects behavioral adaptation, where individuals adjusted to new patterns of movement and interaction, even as restrictions were gradually lifted.

4.2 Response to the COVID-19 pandemic

Based on the observed trends in human mobility and confirmed cases, this section quantifies the responsiveness of mobility behavior to the COVID-19 pandemic using the RI. The RI measures the cumulative degree to which mobility in each category diverged from baseline levels, helping assess how populations adjusted to the unfolding crisis. It is important to note, however, that the RI captures overall responsiveness, not purely voluntary behavioral choices. In many cases, mobility changes were shaped by a combination of individual risk perception and state-imposed policies, such as lockdowns, public gathering restrictions, facility closures, and travel bans.

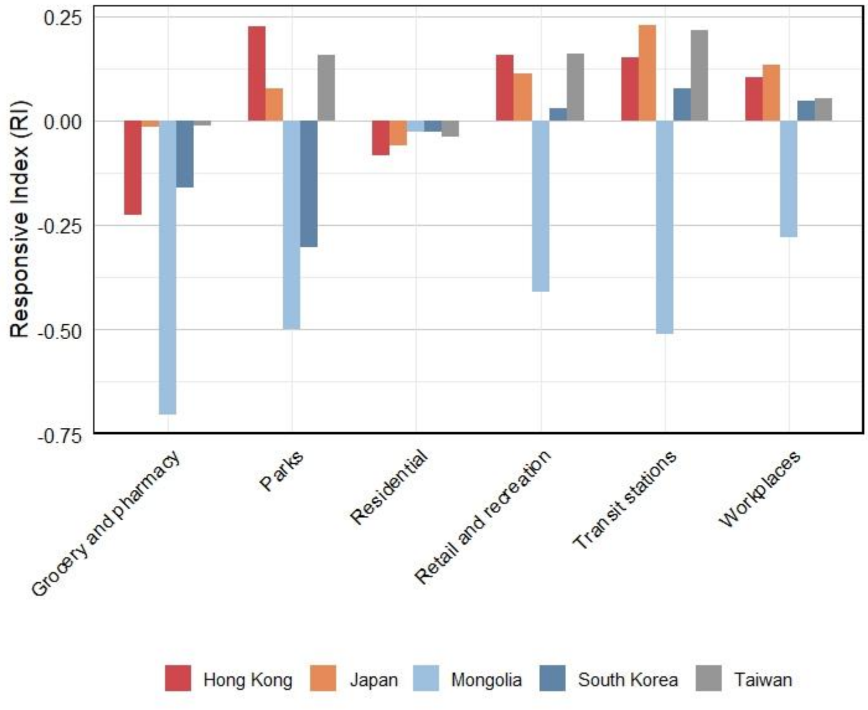

Fig.5 Differential Mobility Category Responses to COVID-19 Measured by RI

The RI analysis provides a quantitative measure of behavioral adjustment magnitude, revealing systematic variations across regions that are interpretable through the dimensions of Behavioral Adaptation Theory. As displayed in Fig.5, across all five regions, the RI shows generally positive responses in categories like transit stations, workplaces, and retail/recreation, indicating reduced mobility consistent with containment goals. This pattern reflects a dominant adaptation strategy of avoidance in response to the perceived high-risk nature of these locations. Conversely, residential mobility showed negative RI values during case surges, signifying the substitution strategy of adapting by shifting activities to the perceived safety of the home. Notably, grocery and pharmacy mobility consistently displayed negative RI (increased activity) across most regions. This divergence underscores a key theoretical insight: adaptation is not a monolithic reduction in all mobility but a strategic re-prioritization. Essential activities persist or intensify, demonstrating how adaptive behavior balances risk appraisal against necessity-driven motivations.

Analyzing the five countries and regions individually, Taiwan (China), Hong Kong, Republic of Korea, and Japan predominantly exhibited positive responses, reflecting widespread adherence to pandemic restrictions. In contrast, mobility behaviors in Mongolia largely exhibited negative feedback, except in the residential category. This displays an adaptation pathway where strong cognitive appraisal of risk led to widespread and behavioral adjustments favoring avoidance and compliance. The positive RI is the quantitative signature of this pervasive adaptive shift. Mongolia's relatively lower confirmed case numbers throughout the study period contributed to this phenomenon, as mobility levels in all categories, except residential, consistently remained above the baseline. This pattern suggests a different cognitive appraisal context, likely shaped by its unique epidemiological trajectory and strict international border controls which may have fostered a perception of relative internal safety.

The RI analysis highlights the critical role of cultural, policy, and pandemic severity factors in shaping mobility responses. For instance, Taiwan (China), Hong Kong, and Republic of Korea implemented stringent restrictions and public health measures, leading to strong positive responses in categories such as transit stations and workplaces. Conversely, Mongolia's less restrictive measures allowed for greater mobility, resulting in a predominantly negative RI across most categories. The findings also align with the Behavioral Adaptation Theory, which posits that individuals adjust their behaviors in response to environmental changes. During the pandemic, as the social environment transformed, individuals became increasingly aware of the risks associated with the virus. This awareness, combined with the growing number of confirmed cases and deaths, prompted significant shifts in mobility behaviors. Mobility patterns revealed a significant shift toward home-based activities, indicating widespread public cooperation with pandemic mitigation efforts. However, grocery and pharmacy visitation patterns diverged from this trend, showing increased mobility driven by essential needs. As pandemic risks escalated, individuals prioritized procuring medical supplies and daily necessities, resulting in heightened activity at these locations. This behavioral dichotomy highlights the nuanced nature of mobility decisions during crises, where urgent requirements may supersede risk avoidance. Thus, the RI does not merely measure response but quantifies the differential outcome of distinct regional adaptation processes, providing empirical evidence for the theory's central premise that behavior adapts in ways that are contingent on environmental and perceptual contexts.

4.3 Detection of changepoint in different categories and countries and regions

To identify when these statistical shifts occurred, we applied the changepoint method to determine the most significant changes across various location categories in the five countries and regions. As shown in Fig.6, changepoints across all six location categories reflect statistically significant changes in mobility behavior. The changepoint analysis provides critical empirical evidence for the temporal dynamics of behavioral adaptation, revealing how the timing, frequency, and magnitude of significant behavioral shifts varied systematically across regions and mobility categories. These variations are not arbitrary but reflect differences in the underlying adaptation processes.

The changepoint analysis reveals distinct patterns in retail and recreation mobility across East Asian regions during the pandemic. Japan and Republic of Korea exhibited relatively stable trajectories with moderate behavioral shifts, while Hong Kong and Taiwan (China) demonstrated more pronounced volatility in this category. Mongolia's changepoints reflected gradual transitions, indicating comparatively limited responsiveness to mobility restrictions. Mongolia exhibited a notable upward trend in this category after the changepoints, reflecting fewer restrictions compared to Japan and Republic of Korea, where grocery and pharmacy mobility showed more fluctuations in response to containment measures. Also, Mobility patterns in parks varied significantly across regions, Japan and Republic of Korea exhibited minimal adaptation in park mobility, while Hong Kong and Taiwan (China) demonstrated notable shifts in response to restrictions and allowances for outdoor activities. Mongolia's mobility patterns in parks showed fewer drastic changes. Transit station mobility displayed substantial adjustments in response to the pandemic, particularly in Hong Kong and Republic of Korea, where sharp declines were observed during peaks in COVID-19 cases. Mongolia, on the other hand, experienced a steep increase in transit mobility after its changepoints, reflecting a faster return to normal commuting patterns compared to the other regions. Workplaces showed varying degrees of mobility adjustments across the five regions. Japan and Republic of Korea displayed consistent but small dips in workplace mobility, aligning with remote work policies. Furthermore, residential mobility changepoints highlighted significant increases in time spent at home, particularly during lockdown periods. Taiwan (China) and Hong Kong experienced strong changepoints in this category, indicating adherence to stay-at-home measures. Conversely, Mongolia displayed less dramatic shifts, reflecting a lower overall impact of the pandemic on residential behavior.

The occurrence of changepoints signifies not only substantial behavioral transformations but also the evolving public perceptions of the pandemic, transitioning from initial panic to adaptive responses (Weitz et al., 2020). Transit stations and workplaces saw substantial, often synchronous negative changepoints across multiple regions, underscoring a widespread adaptive strategy of avoidance for high-risk, non-essential shared spaces. Residential mobility showed strong positive changepoints during lockdowns, marking clear shifts toward the substitution strategy of using the home as a primary activity hub. Park mobility displayed divergent changepoint patterns, highlighting how the same category could be appraised differently leading to region-specific adaptive strategies. In summary, the changepoint analysis operationalizes the "when" and "how suddenly" of behavioral adaptation. The distinct regional types empirically validate that there is no single adaptive response. Instead, the timing and nature of behavioral transitions are contingent on how regional contexts shape the collective cognitive appraisal of risk and the subsequent selection and persistence of behavioral adjustment strategies (Dehning et al., 2020). This moves the findings beyond descriptive chronology to a theory-grounded explanation of differential adaptation tempo and stability.

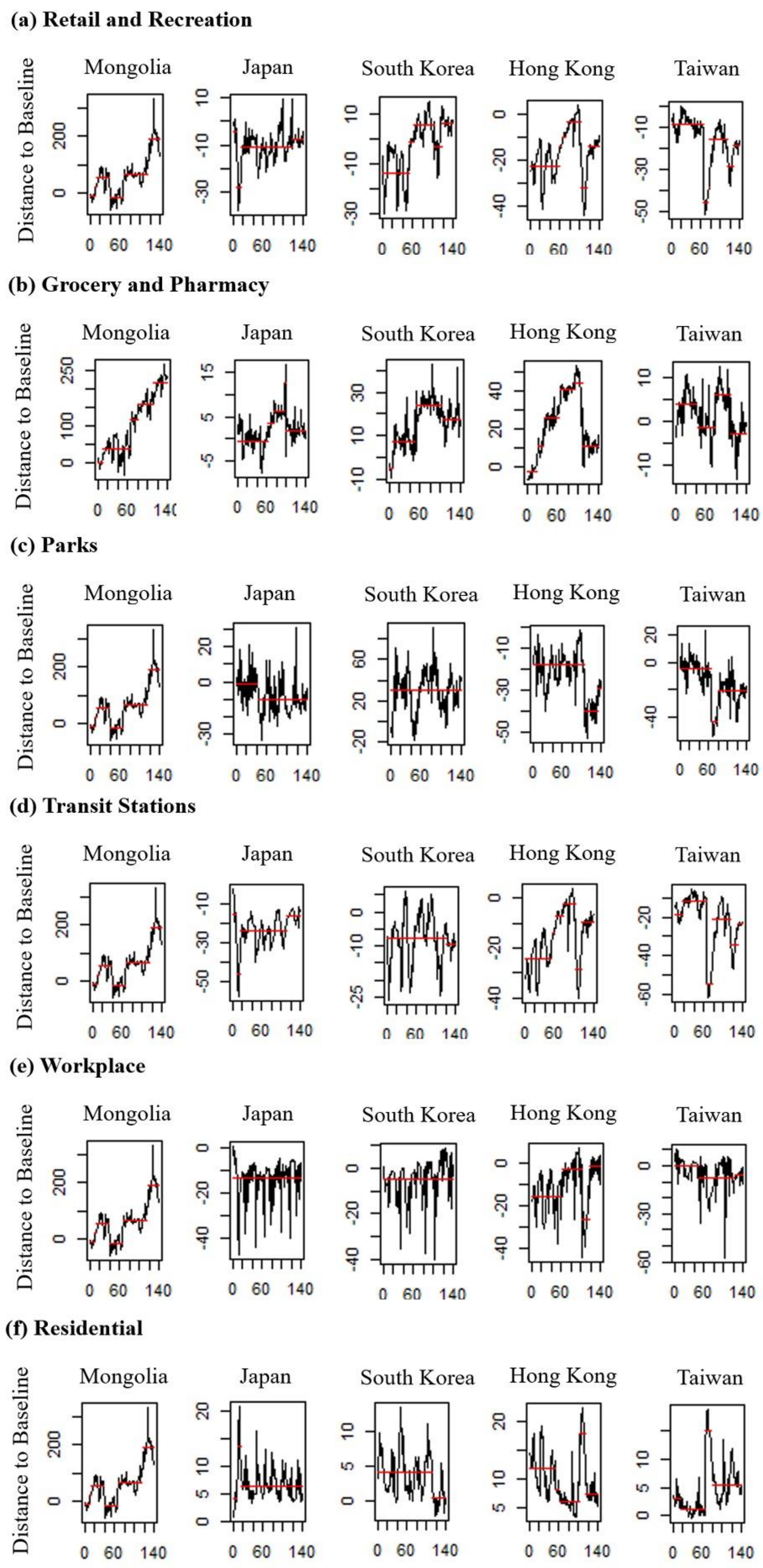

Fig.6 Detection of the changepoint across six different locations (red lines indicate statistically significant

changepoints)

4.4 The impact of human mobility behavior on economic forecasting

Building upon the distinct behavioral adaptation pathways identified across the five regions, the analysis of economic forecasting models reveals that these adaptive patterns have tangible and differential impacts on economic predictability. The features selected as most important for forecasting in each region are not generic but reflect the specific nature and stability of their dominant adaptation strategy.

In general, the relative importance of mobility categories varied across the five East Asian countries and regions. Mobility in retail and recreation, transit stations, and workplaces exhibited the strongest influence on economic outcomes, reflecting their critical roles in driving consumer spending, transportation, and labor productivity. Conversely, residential mobility had a less pronounced impact on economic performance, as increased time spent at home often signals reduced economic activity.

As illustrated in Fig.7, the model measures the contribution of each feature to its predictions, with higher values indicating greater importance. lag=N denotes a time-lagged mobility feature representing data from N days prior to the target economic indicator. And these lags capture the delayed economic impact of mobility changes. MSE values were all close to 0, indicating good model performance. In Mongolia, the high gain of the lag=14 feature (0.938056078) suggests that mobility data from the past 14 days is critical for economic forecasting. Other features, such as parks, residential, and retail and recreation, also show notable contributions, indicating their roles in predicting economic activity. For Japan, changes in mobility behavior 10 days prior significantly impact current economic conditions. Features such as grocery and pharmacy, retail and recreation, and parks also contribute. In Republic of Korea and Hong Kong, the lag=7 feature is particularly significant, indicating that mobility data from the past 7 days is crucial for forecasting current economic activity. In Republic of Korea, mobility in transit stations and retail and recreation is important, reflecting the impact of commuting, travel, and consumer behavior on economic activity. In Hong Kong, mobility in workplaces and parks is significant, indicating the importance of work, production, leisure, and tourism activities on the economy. Taiwan (China) exhibited the shortest lag time (4 days). The high gain of lag=4 indicates that recent data is crucial, possibly reflecting short-term cyclical changes in economic activity between weekdays and weekends. Retail and recreation, as well as parks, also impact economic activity in Taiwan (China).

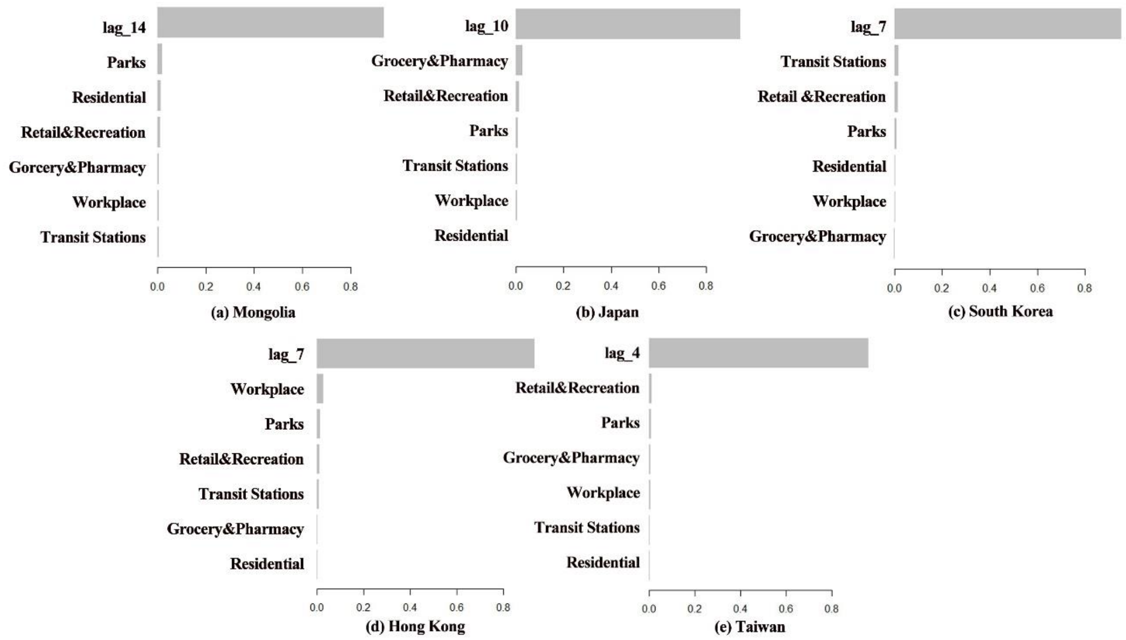

Fig.7 Feature importance for GBM Model across countries and regions

Firstly, lagged features in human mobility data, such as trends in mobility over the past few days, demonstrate significant importance in predictive models across different countries and regions. This reflects that economic activities exhibit certain cyclicality and inertia, where past mobility patterns have a decisive impact on economic conditions. Hong Kong and Republic of Korea show that mobility behavior from the past week (lag=7) plays a crucial role in economic forecasts, likely linked to the stability of surrounding environments, social activities, and consumer behavior. Secondly, consumer behavior plays a critical role in economic forecasting. During economic recessions or recoveries, the level of consumer participation in retail and recreation activities directly influences the speed and strength of economic recovery. Thirdly, changes in mobility related to work and production activities also have a significant impact on economic forecasting. Mobility from workplaces reflect labor activity and productivity levels, directly influencing a country or region's economic growth. Additionally, changes in mobility at transportation hubs and public service facilities provide important clues for economic forecasting. In essence, the analysis demonstrates that the link between mobility and economic outcomes is not uniform but is filtered through the lens of behavioral adaptation. The cognitive appraisal of risk and the resulting behavioral adjustment strategies reshape the very structure of the economy. Consequently, the most informative features for economic forecasting in a given region are those that best capture the signature of its dominant adaptive pathway.

Therefore, a theoretically informed understanding of mobility behavior that distinguishes short-term reactions from longer-term adaptations is crucial not only for interpreting past economic impacts but also for constructing more accurate and context-sensitive predictive models. By integrating Behavioral Adaptation Theory, we move beyond merely noting that mobility features influence the economy to explaining why specific features exert stronger effects in some regions than in others, as determined by the ingrained adaptive behaviors of their populations.

5 Discussion

5.1 Contributions

This study examines human mobility behavior across five East Asian countries and regions during the COVID-19 pandemic, integrating Behavioral Adaptation Theory with mobility data to establish a novel analytical framework. First, it presents a focused analysis of human mobility across five East Asian societies during the pandemic, offering comparative insights shaped by varied government policies and cultural contexts. Second, it applies advanced analytical techniques to identify critical periods of behavioral change and to enhance the accuracy of economic forecasts linked to mobility dynamics. Third, it grounds its empirical findings within Behavioral Adaptation Theory, providing a robust framework for understanding pandemic-induced mobility shifts and their broader societal implications.

To integrate the empirical findings with Behavioral Adaptation Theory, we explicitly situate the results within the framework's key dimensions. The empirical indicators employed in this study operationalize these adaptive processes in complementary ways: the Responsive Index reflects the cumulative degree of behavioral adjustment relative to baseline norms; changepoints capture temporal thresholds where new information or policy cues trigger reassessment and behavioral updating; and category-specific mobility trajectories reveal how individuals reconfigure daily routines in response to shifting environmental and social constraints. These measures allow us to interpret cross-regional differences not merely descriptively but as distinct manifestations of adaptive pathways shaped by the interplay of perceived risk, cultural expectations of compliance, policy stringency, and infrastructural dependence on particular mobility modes.

5.2 Contextualizing the Findings: Commonalities and Divergences

Interpreted through the lens of Behavioral Adaptation Theory, the cross-regional variation in mobility behavior reflects distinct adaptive pathways shaped by differences in cognitive risk assessment, normative expectations, environmental constraints, and policy regimes. Mongolia's comparatively stable mobility patterns indicate a weaker activation of adaptive mechanisms, consistent with lower perceived risk and limited disruption to established routines. In contrast, Japan and Republic of Korea, characterized by dense urban settings and high transit dependency, showed sharp declines in workplace and transit mobility. This reflects behavioral adjustments driven by greater sensitivity to higher perceived vulnerability. Taiwan (China) and Republic of Korea further demonstrated adaptation strengthened by strong normative pressures and collectivist compliance cultures, which accelerated compliance with restrictions and helped sustain reduced levels of non-essential mobility. Hong Kong's sharper volatility reflects an adaptation pathway dominated by abrupt policy shifts and fluctuating perceptions of institutional control. These differences underscore that behavioral adaptation is inherently multi-scalar, emerging from the joint influence of perceived risk, cultural expectations of compliance, policy stringency, and the built environment, rather than from any single determinant.

Findings on the pandemic's significant influence on human mobility in East Asia are effectively framed by Behavioral Adaptation Theory. This theory explains how individuals modify their behaviors in response to environmental changes, such as the risks and restrictions introduced by COVID-19. The observed consistent increases in residential time and decreases in transit and workplace mobility across most regions reflect public compliance with health measures and cognitive adjustments to reduce exposure. Regional variations further emphasize the role of context. Mongolia's stable mobility levels can be linked to its geographic isolation and early containment success, coupled with lower urban density and transit reliance which reduced the perceived need for drastic behavioral change. Japan and Taiwan (China) showed more sustained reductions, driven by strong social norms and risk aversion in Japan, and by a proactive, technology-enabled containment strategy paired with high public trust in Taiwan (China). Republic of Korea presented a hybrid approach, employing digital surveillance while maintaining moderate activity levels through targeted restrictions rather than blanket lockdowns. Hong Kong displayed volatile patterns, with sharp drops during outbreaks followed by partial rebounds.

An important question arising from our findings is whether these mobility shifts represent short-term compliance or longer-term behavioral change. Although data conclude in October 2022, patterns in certain categories, especially workplace and transit mobility, suggest the beginning of lasting shifts. The persistence of reduced mobility in Japan and Taiwan (China) well into late 2022 points to potential structural changes that may extend beyond the immediate pandemic response. Contrary to the general decline in non-essential mobility, visits to grocery and pharmacy locations paradoxically increased during the pandemic. Findings show that mobility to these essential venues not only remained above baseline but continued rising during peak infection waves in Mongolia and Taiwan (China). This suggests that as other activities contracted, essential shopping became more frequent and concentrated, potentially creating unintended transmission risks, a concern supported by studies linking retail density to infection clusters (Nanda et al., 2022). Conversely, research in European contexts estimates that reduced mobility in this category accounted for most of the decrease in deaths (Bryant and Elofsson, 2020), highlighting its critical role. The distinction between short-term reaction and longer-term adaptation is central to the interpretation of pandemic mobility patterns. In Behavioral Adaptation Theory, short-term reactions reflect rapid, situational adjustments tied to policy stringency or sudden risk escalation, whereas long-term adaptations emerge when behaviors persist after acute triggers diminish. The dataset reveals that certain mobility categories, particularly those related to transit and workplaces in Japan and Taiwan (China), show patterns which persist well beyond episodic surges in cases; this points to the development of more stabilized, long-term adaptations. By contrast, Mongolia's mobility oscillations are more consistent with short-term reactive cycles that reset to baseline after each outbreak period. Republic of Korea and Hong Kong exhibit mixed trajectories: sharp mobility contractions during peak waves followed by partial rebounds, suggesting transitional stages of adaptation rather than fully stabilized shifts. Although our data end in October 2022 and cannot capture full post-pandemic normalization, the persistence of these multi-year patterns supports the interpretation that some behavioral changes were evolving into longer-term adaptations rather than remaining transient reactions.

Under Behavioral Adaptation Theory, mobility shifts are closely tied to the social environment (Bavel et al., 2020). Changepoints capture how populations perceive and respond to risk, providing valuable information for timely policy adjustment and resource allocation (Yang et al., 2021). Our changepoint analysis across the five regions revealed significant differences in mean mobility before and after these points, while standard deviation showed more subtle variations. This contrasts with Panik et al. (2023), whose analysis of travel behavior in Bibb County and Huron County found significant differences in standard deviation.

5.3 Implications, Limitations, and Future Research

While our analysis primarily attributes mobility changes to COVID-19-related policies and perceptions, we acknowledge concurrent influences such as remote work expansion, economic slowdowns, fuel price fluctuations, and pandemic-unrelated consumer shifts. The findings hold key implications for public health and economic policies. Increased residential mobility during COVID-19 peaks confirms the effectiveness of stay-at-home measures in curbing transmission, underscoring the value of timely, targeted interventions in health crises. Divergent mobility patterns across categories highlight the need to balance restrictions with essential needs by way of example: increased grocery/pharmacy mobility due to necessity, suggesting policies like supporting grocery delivery or extending pharmacy hours to minimize unnecessary movement. Economically, reduced workplace and transit mobility significantly impacted performance, especially in highly urbanized, public transit-dependent regions. Long-term mobility adaptations demand forward-thinking policies in urban planning, public transit, and labor markets to support sustainable recovery.

Despite the valuable insights from this study, several limitations warrant attention in future research. A key factor influencing mobility patterns during the COVID-19 pandemic was the variation in government containment policies. Future research could integrate quantitative policy indices to better disentangle top-down policy effects from bottom-up behavioral adaptation, thereby providing a clearer understanding of compliance, resistance, or fatigue over time. Moreover, comparative studies could further examine the spatiotemporal dynamics of mobility adaptation by analyzing behavioral responses across different pandemic waves and geographical settings. As shown by Kan et al. (2021) and Yu and Liu (2023), responses varied both temporally and culturally, underscoring the need to investigate how urban structures and governance systems shape these differences.

6 Conclusions

This study investigated human mobility behavior during the COVID-19 pandemic across five East Asian countries and regions-Mongolia, Japan, Republic of Korea, Hong Kong, and Taiwan (China)-using Community Mobility Report, RI metrics, and changepoints detection methods. By analyzing mobility patterns in six categories (retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas), we identified key behavioral shifts, explored their temporal dynamics, and assessed their economic implications.

(1) Mobility adaptation varied significantly across regions, shaped by differences in policy stringency, cultural norms, and the progression of COVID-19 outbreaks. Mongolia exhibited relatively stable patterns, while Hong Kong, Taiwan (China), Japan, and Republic of Korea showed more pronounced reductions in public activity during case surges.

(2) Changepoint analysis revealed that behavioral significant shifts, though the timing and magnitude of adaptation differed across categories and regions. Notably, residential mobility increased across all regions during outbreak phases, indicating widespread compliance with or adaptation to stay-at-home expectations.

(3) The RI offered a useful summary of mobility responsiveness, showing that most regions responded positively in high-contact categories. However, essential needs such as grocery and pharmacy visits continued to drive mobility in defiance of broader restrictions, revealing a layered pattern of adaptation that blended necessity with compliance.

(4) The GBM model revealed that mobility data were predictive of short-term changes in GDP and unemployment. Specifically, data from the retail, transit, and workplace categories showed strong predictive power. Furthermore, the inclusion of lagged mobility features enhanced the model’s sensitivity to delayed economic responses.

While our dataset extends to October 2022, we emphasize that this period represents only the later stages of the pandemic and the early signs of partial reopening, rather than full economic or social recovery. As such, the trends observed in this study should be interpreted as indicators of transitional mobility behavior and evolving economic conditions, not definitive endpoints. Overall, this study contributes to understanding how human mobility responds to systemic shocks and offers a transferable framework integrating behavioral theory, mobility data, and economic forecasting. The analytical tools applied here may prove valuable in preparing for future crises, ranging from health-related to other types, where adaptation, resilience, and behavior are central to shaping outcomes. The distinction between short-term behavioral reactions and emerging long-term adaptations holds particular importance for policymaking. Evidence indicates that although some mobility patterns were transient and tied to outbreak dynamics, others solidified into new norms, specifically within transit and workplace behaviors, thereby signaling deeper adaptive shifts beyond temporary compliance. Acknowledging this divergence is vital for formulating sustainable post-crisis policies across mobility, transportation, and economic domains.

Data Availability

The data are available from the corresponding author, upon reasonable request.

Competing interests

The authors have no competing interests to declare that are relevant to the content of this article.

Ethics Statement

This article does not contain any studies with human participants performed by any of the authors.

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Reference

Aktay, A., Bavadekar, S., Cossoul, G., Davis, J., Desfontaines, D., Fabrikant, A., ... & Wilson, R. J. (2020). Google COVID-19 community mobility reports: anonymization process description (version 1.1). https://doi.org/10.48550/arXiv.2004.04145.

Bavel, J. J. V., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., ... & Willer, R. (2020). Using social and behavioural science to support COVID-19 pandemic response. *Nature human behaviour*, 4(5), 460-471. https://doi.org/10.1038/s41562-020-0884-z.

Bamney, A., Jashami, H., Sonduru Pantangi, S., Ambabo, J., Megat-Johari, M. U., Cai, Q., ... & Savolainen, P. T. (2023). Examining impacts of COVID-19-related stay-at-home orders through a two-way random effects model. *Transportation Research Record*, 2677(4), 255-266.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., ... & Pammolli, F. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the national academy of sciences*, 117(27), 15530-15535. https://doi.org/10.1073/pnas.2007658117.

Bryant, P., & Elofsson, A. (2020). Estimating the impact of mobility patterns on COVID-19 infection rates in 11 European countries. *PeerJ*, 8, e9879. https://doi.org/10.7717/peerj.9879.

Cao, L., & Liu, Q. (2024). COVID-19 modeling: A review. *ACM Computing Surveys*, 57(1), 1-42. https://doi.org/10.1145/3686150.

Champlin, C., Sirenko, M., & Comes, T. (2023). Measuring social resilience in cities: An exploratory spatio-temporal analysis of activity routines in urban spaces during Covid-19. *Cities*, 135, 104220. https://doi.org/10.1016/j.cities.2023.104220.

Chapin, C., & Roy, S. S. (2021). A spatial web application to explore the interactions between human mobility, government policies, and COVID-19 cases. *Journal of Geovisualization and Spatial Analysis*, 5, 1-8. https://doi.org/10.1007/s41651-021-00081-y.

Chen, S., Ding, F., Buil-Gil, D., Hao, M., Maystadt, J. F., Fu, J., ... & Jiang, D. (2024). The impact of COVID-19 lockdown on fraud in the UK. *Humanities and Social Sciences Communications*, *11*(1), 1-11. https://doi.org/10.1057/s41599-024-04201-z.

Chen, Y., Chen, M., Huang, B., Wu, C., & Shi, W. (2021). Modeling the spatiotemporal association between COVID‐19 transmission and population mobility using geographically and temporally weighted regression. *GeoHealth*, 5(5), e2021GH000402. https://doi.org/10.1029/2021GH000402.

Dehning, J., Zierenberg, J., Spitzner, F. P., Wibral, M., Neto, J. P., Wilczek, M., & Priesemann, V. (2020). Inferring change points in the spread of COVID-19 reveals the effectiveness of interventions. *Science*, 369(6500), eabb9789. https://doi.org/10.1126/science.abb9789.

Doornik, J. A., Castle, J. L., & Hendry, D. F. (2021). Modeling and forecasting the COVID‐19 pandemic time‐series data. *Social science quarterly*, 102(5), 2070-2087. https://doi.org/10.1111/ssqu.13008.

Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of statistics*, 1189-1232.

Fumagalli, L. A. W., Rezende, D. A., & Guimarães, T. A. (2021). Challenges for public transportation: Consequences and possible alternatives for the Covid-19 pandemic through strategic digital city application. *Journal of Urban Management*, 10(2), 97-109. https://doi.org/10.1016/j.jum.2021.04.002.

Golledge, R. G. (1997). Spatial behavior: A geographic perspective. Guilford Press.

Gu, H., Shen, J., & Chu, J. (2023). Understanding intercity mobility patterns in rapidly urbanizing China, 2015–2019: evidence from longitudinal poisson gravity modeling. *Annals of the American Association of Geographers*, 113(1), 307-330. https://doi.org/10.1080/24694452.2022.2097050.

Gu, H., Lin, Y., Hu, H., & Yu, H. (2025). COVID-19 pandemic and road infrastructure exerted stage-dependent spatiotemporal influences on inter-city road travel in China. *Humanities and Social Sciences Communications*, 12(1), 1-13. https://doi.org/10.1057/s41599-025-05018-0.

Hajlasz, M., & Pei, S. (2024). Predictability of human mobility during the COVID-19 pandemic in the United States. *PNAS nexus*, 3(8), 308. https://doi.org/10.1093/pnasnexus/pgae308.

Haldane, V., De Foo, C., Abdalla, S. M., Jung, A. S., Tan, M., Wu, S., ... & Legido-Quigley, H. (2021). Health systems resilience in managing the COVID-19 pandemic: lessons from 28 countries. *Nature medicine*, 27(6), 964-980. https://doi.org/10.1038/s41591-021-01381-y.

Hamilton, M., Fischer, A. P., Guikema, S. D., & Keppel‐Aleks, G. (2018). Behavioral adaptation to climate change in wildfire‐prone forests. *Wiley Interdisciplinary Reviews: Climate Change*, 9(6), e553. https://doi.org/10.1002/wcc.553.

Hasselwander, M., Tamagusko, T., Bigotte, J. F., Ferreira, A., Mejia, A., & Ferranti, E. J. (2021). Building back better: The COVID-19 pandemic and transport policy implications for a developing megacity. *Sustainable Cities and Society*, 69, 102864. https://doi.org/10.1016/j.scs.2021.102864.

Hayakawa, K., Mukunoki, H., & Urata, S. (2023). Can e-commerce mitigate the negative impact of COVID-19 on international trade?. *The Japanese Economic Review*, 74(2), 215-232. https://doi.org/10.1007/s42973-021-00099-3.

Hinkley, D. V. (1970). Inference about the change-point in a sequence of random variables, 1-17. https://doi.org/10.1093/biomet/57.1.1.

Huang, Z., Ling, X., Wang, P., Zhang, F., Mao, Y., Lin, T., & Wang, F. Y. (2018). Modeling real-time human mobility based on mobile phone and transportation data fusion. *Transportation research part C: emerging technologies*, 96, 251-269. https://doi.org/10.1016/j.trc.2018.09.016.

Huang, X., Li, Z., Jiang, Y., Ye, X., Deng, C., Zhang, J., & Li, X. (2021). The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the US during the COVID-19 pandemic. *International Journal of Digital Earth*, 14(4), 424-442. https://doi.org/10.1080/17538947.2021.1886358.

Hu, S., Xiong, C., Yang, M., Younes, H., Luo, W., & Zhang, L. (2021). A big-data driven approach to analyzing and modeling human mobility trend under non-pharmaceutical interventions during COVID-19 pandemic. *Transportation Research Part C: Emerging Technologies*, 124, 102955. https://doi.org/10.1016/j.trc.2020.102955.

Hu, S., Xiong, C., Younes, H., Yang, M., Darzi, A., & Jin, Z. C. (2022). Examining spatiotemporal evolution of racial/ethnic disparities in human mobility and COVID-19 health outcomes: Evidence from the contiguous United States. *Sustainable Cities and Society*, 76, 103506. https://doi.org/10.1016/j.scs.2021.103506.

Jin, H., Li, X., Huang, Y., Yang, C., Armoogum, S., Xiong, N., & Wu, W. (2024). The interplay of time and space in human behavior: a sociological perspective on the TSCH model. Humanities and Social Sciences Communications, 11(1), 1-17. https://doi.org/10.1057/s41599-024-04274-w

Kan, Z., Kwan, M. P., Huang, J., Wong, M. S., & Liu, D. (2021). Comparing the space‐time patterns of high‐risk areas in different waves of COVID‐19 in Hong Kong. *Transactions in GIS*, 25(6), 2982-3001. https://doi.org/10.1111/tgis.12800.

Killick, R., & Eckley, I. (2014). Changepoint: An R package for changepoint analysis. *Journal of statistical software*, 58(3), 1-19. https://doi.org/10.18637/jss.v058.i03.

Kraemer, M. U., Yang, C. H., Gutierrez, B., Wu, C. H., Klein, B., Pigott, D. M., ... & Scarpino, S. V. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science*, 368(6490), 493-497. https://doi.org/10.1126/science.abb4218.

Long, Y., Han, H., Tu, Y., & Shu, X. (2015). Evaluating the effectiveness of urban growth boundaries using human mobility and activity records. *Cities*, 46, 76-84. https://doi.org/10.1016/j.cities.2015.05.001.

Nanda, R. O., Nursetyo, A. A., Ramadona, A. L., Imron, M. A., Fuad, A., Setyawan, A., & Ahmad, R. A. (2022). Community mobility and COVID-19 dynamics in Jakarta, Indonesia. *International Journal of Environmental Research and Public Health*, 19(11), 6671. https://doi.org/10.3390/ijerph19116671.

Okamoto, S. (2022). State of emergency and human mobility during the COVID-19 pandemic in Japan. Journal of Transport & Health, 26, 101405. https://doi.org/10.1016/j.jth.2022.101405.

Osman, M. (2010). Controlling uncertainty: a review of human behavior in complex dynamic environments. *Psychological bulletin,* 136(1), 65. https://doi.org/10.1037/a0017815.

Panik, R. T., Watkins, K., & Ederer, D. (2023). Metrics of Mobility: Assessing the Impact of COVID-19 on Travel Behavior. *Transportation Research Record*, 2677(4), 583-596. https://doi.org/10.1177/03611981221131812.

Pavlović, T., Azevedo, F., De, K., Riaño-Moreno, J. C., Maglić, M., Gkinopoulos, T., ... & Keudel, O. (2022). Predicting attitudinal and behavioral responses to COVID-19 pandemic using machine learning. *PNAS nexus*, 1(3), pgac093. https://doi.org/10.1093/pnasnexus/pgac093.

Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: a population-based study. *The Lancet Digital Health*, 2(12), e638-e649. https://doi.org/10.1016/S2589-7500(20)30243-0.

Rachman, I. (2025). Cognitive and Behavioral Adaptation Strategies in Learning Financial Derivatives: A Qualitative

Study on Undergraduate Students. Daengku: *Journal of Humanities and Social Sciences Innovation*, 5(2), 310-319. https://doi.org/10.35877/454RI.daengku3892.

Rafiq, R., McNally, M. G., Uddin, Y. S., & Ahmed, T. (2022). Impact of working from home on activity-travel behavior during the COVID-19 Pandemic: An aggregate structural analysis. *Transportation Research Part A: Policy and Practice*, 159, 35-54. https://doi.org/10.1016/j.tra.2022.03.003.

Rowe, F., Calafiore, A., Arribas‐Bel, D., Samardzhiev, K., & Fleischmann, M. (2023). Urban exodus? Understanding human mobility in Britain during the COVID‐19 pandemic using Meta‐Facebook data. *Population, Space and Place*, 29(1), e2637. https://doi.org/10.1002/psp.2637.

Sih, A., Ferrari, M. C., & Harris, D. J. (2011). Evolution and behavioural responses to human‐induced rapid environmental change. *Evolutionary applications*, 4(2), 367-387. https://doi.org/10.1111/j.1752-4571.2010.00166.x.

Sun, X., Wei, Y., & Song, W. (2024). Tracking Global Changes of Human Mobility Behavior and Resilience during the COVID-19 Pandemic. *Papers in Applied Geography*, 1-17. https://doi.org/10.1080/23754931.2024.2361236.

Tirachini, A., & Cats, O. (2020). COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of public transportation*, 22(1), 1-21. https://doi.org/10.5038/2375-0901.22.1.1.

Vanhove, M. P., Thys, S., Decaestecker, E., Antoine-Moussiaux, N., De Man, J., Hugé, J., ... & Janssens de Bisthoven, L. (2021). Global change increases zoonotic risk, COVID-19 changes risk perceptions: a plea for urban nature connectedness. *Cities & health*, 5(sup1), S131-S139. https://doi.org/10.1080/23748834.2020.1805282.

Verschuur, J., Koks, E. E., & Hall, J. W. (2021). Observed impacts of the COVID-19 pandemic on global trade. *Nature Human Behaviour*, 5(3), 305-307. https://doi.org/10.1038/s41562-020-0896-8.

Wang, A., Zhang, A., Chan, E. H., Shi, W., Zhou, X., & Liu, Z. (2020). A review of human mobility research based on big data and its implication for smart city development. *ISPRS International Journal of Geo-Information*, 10(1), 13. http://doi.org/10.3390/ijgi10010013.

Weitz, J. S., Park, S. W., Eksin, C., & Dushoff, J. (2020). Awareness-driven behavior changes can shift the shape of epidemics away from peaks and toward plateaus, shoulders, and oscillations. *Proceedings of the National Academy of Sciences,* 117(51), 32764-32771. https://doi.org/10.1073/pnas.2009911117.

Xu, F., Wang, Q., Moro, E., Chen, L., Salazar Miranda, A., González, M. C., ... & Evans, J. (2025). Using human mobility data to quantify experienced urban inequalities. *Nature Human Behaviour*, 1-11. https://doi.org/10.1038/s41562-024-02079-0.

Yang, M., Han, C., Cui, Y., & Zhao, Y. (2021). COVID-19 and mobility in tourism cities: A statistical change-point detection approach. *Journal of Hospitality and Tourism Management*, 47, 256-261. https://doi.org/10.1016/j.jhtm.2021.03.014.

Yang, Z. (2024). How east Asian culture influences the personality traits of its residents: an exploration of cultural characteristics and the emphasis on interdependence. *Communications in Humanities Research*, 31, 44-50. https://doi.org/10.54254/2753-7064/31/20231831.

Yeung, H. W. C. (2022). Explaining geographic shifts of chip making toward East Asia and market dynamics in semiconductor global production networks. Economic Geography, 98(3), 272-298. https://doi.org/10.1080/00130095.2021.2019010.

Yu, Z., & Liu, X. (2023). Spatial variations of the third and fourth COVID-19 waves in Hong Kong: A comparative study using built environment and socio-demographic characteristics. *Environment and Planning B: Urban Analytics and City Science*, 50(5), 1144-1160. https://doi.org/10.1177/23998083221107019.

Yu, S., Mückschel, M., Hoffmann, S., Bluschke, A., Pscherer, C., & Beste, C. (2023). The neural stability of perception–motor representations affects action outcomes and behavioral adaptation. *Psychophysiology*, 60(1), e14146. https://doi.org/10.1111/psyp.14146.

Zabaniotou, A. (2020). A systemic approach to resilience and ecological sustainability during the COVID-19 pandemic: Human, societal, and ecological health as a system-wide emergent property in the Anthropocene. *Global transitions*, 2, 116-126. https://doi.org/10.1016/j.glt.2020.06.002.

Zbezhkhovska, U., & Chumachenko, D. (2025). Smoothing Techniques for Improving COVID-19 Time Series Forecasting Across Countries. *Computation*, 13(6), 136. https://doi.org/10.3390/computation13060136.

Zhao, P., Liu, Q., Ma, T., Kang, T., Zhou, Z., Liu, Z., ... & Wan, J. (2023). Policy instruments facilitate China's COVID-19 work resumption. *Proceedings of the National Academy of Sciences*, 120(41), e2305692120. https://doi.org/10.1073/pnas.2305692120.

Zheng, Z., Xie, Z., Qin, Y., Wang, K., Yu, Y., & Fu, P. (2021). Exploring the influence of human mobility factors and spread prediction on early COVID-19 in the USA. *BMC Public Health*, 21, 1-13. https://doi.org/10.1186/s12889-021-10682-3.

Zheng, Y., Yue, K., Wong, E. W., & Yuan, H. Y. (2025). Impact of human mobility and weather conditions on Dengue mosquito abundance during the COVID-19 pandemic in Hong Kong. *Infectious Disease Modelling*, 10(3), 840-849. https://doi.org/10.1016/j.idm.2025.04.002.