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RESEARCH ARTICLE

# Predicting households' residential mobility trajectories with geographically localized interpretable model-agnostic explanation (GLIME)

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**ABSTRACT**

Human mobility analytics using artificial intelligence (AI) has gained significant attention with advancements in computational power and the availability of high-resolution spatial data. However, the application of deep learning in social sciences and human geography remains limited, primarily due to concerns with model explainability. In this study, we employ an explainable GeoAI approach called geographically localized interpretable model-agnostic explanation (GLIME) to explore human mobility patterns over large spatial and temporal extents. Specifically, we develop a two-layered long short-term memory (LSTM) model capable of predicting individual-level residential mobility patterns across the United States from 2012 to 2019. We leverage GLIME to provide geographical perspectives and interpret deep neural networks at the state level. The results reveal that GLIME enables spatially explicit interpretations of local impacts attributed to different variables. Our findings underscore the significance of considering path dependency in residential mobility dynamics. While the prediction of complex human spatial decision-making processes still presents challenges, this research demonstrates the utility of deep neural networks and explainable GeoAI to support human dynamics understanding. It sets the stage for further finely tuned investigations in the future, promising deep insights into intricate mobility phenomena.

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**KEYWORDS**
Explainable GeoAI; model-agnostic explanation; long short-term memory (LSTM); trajectory prediction; residential mobility

## 1. Introduction

Residential mobility, the relocation of individuals and households from one dwelling to another, offers valuable insights into the intricate interplay of socioeconomic dynamics, environmental exposures, and urban development. The research area has attracted sustained attention across diverse social science disciplines, including

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geography, sociology, and economics, as evidenced by seminal works of Rossi (1955), Schelling (1969), and others. Residential mobility not only represents potential changes in socioeconomic opportunities (Winstanley *et al.* 2002, Jelleyman and Spencer 2008) and long-term exposure to environmental variables (Brokamp *et al.* 2016) at an individual level but also touches on urban typologies (South and Crowder 1997b, Torrens and Nara 2007, Cooke 2010, Sharkey 2012) and local housing/labor markets (Van der Vlist *et al.* 2002) at the collective level.

With recent advancements in geospatial understanding, GeoAI has contributed remarkable progress in prediction accuracy across various domains, particularly health (VoPham *et al.* 2018, Kamel Boulos *et al.* 2019), land use changes (Gebru *et al.* 2017, Helber *et al.* 2019), and urban dynamics (Grekousis 2019, Yun *et al.* 2020). Deep neural networks have been applied to analyze a huge amount of individual-level human mobility data to predict trajectories (Li *et al.* 2021, Hagenauer and Helbich 2022). The models have proven accurate in predicting individual trajectories at small spatiotemporal scales by considering prior movements and social interactions (Xu *et al.* 2018, Ip *et al.* 2021, Yin *et al.* 2023).

However, despite considerable strides in predicting short-term individual trajectories, there remains a scarcity of research utilizing deep learning techniques to forecast long-term residential mobility. The prevailing approach has treated residential mobility from a macroscopic perspective where individual moves are aggregated into origin and destination (OD) flows (Robinson and Dilkina 2018, Xu *et al.* 2019, Golenvaux *et al.* 2020). This limitation stems from a dearth of large-scale individual-level datasets on residential mobility and the inherent lack of explainability in GeoAI models (Li 2020, Xing and Sieber 2023).

Prior investigations into individual residential mobility have relied on datasets with either limited spatial coverage or small sample sizes, which constrained the development and validation of deep learning models. For instance, empirical studies in the United States often drew upon city-level survey data (Clark and Ledwith 2006, Sampson and Sharkey 2008), providing insights within confined geographic boundaries. While the Panel Study of Income Dynamics (PSID) has tracked household residential trajectories for over 50 years, its small sample size (fewer than 10,000 households) cannot be taken as representative of the entire US population (Johnson *et al.* 2018).

The complexity of deep neural networks has enabled non-linear combinations of input features beyond the reach of static equations but has hindered their ability to offer comprehensible explanations of model outcomes. The difficulty in explanation from deep neural networks has limited their applicability to social sciences and human geographic studies, which strive to elucidate underlying mechanisms through the examination of socioeconomic relationships (Jin 2022) rather than solely focusing on predictive tasks. To address this "black-box" issue, explainable artificial intelligence (XAI) has emerged as a prominent area of research (Samek *et al.* 2017).

In the domain of geography, researchers have proposed various methodologies to shed light on variable contributions and model internals (Cheng *et al.* 2021, Yudistira *et al.* 2021, Hagenauer and Helbich 2022). Model-agnostic and local explanations, such as local interpretable model-agnostic explanations (LIME) have attracted increasing attention due to their potential to enhance the understanding of input–output relationships by perturbing models (van der Velden *et al.* 2022, Xing and Sieber 2023). LIME, introduced by Ribeiro *et al.* (2016), has proven effective in explaining latent inference mechanisms within various studies by approximating local simple models using a range of data that brings a huge, complex model to an interpretable level (Parmar *et al.* 2021, Shams Amiri *et al.* 2021, Viana *et al.* 2021). Nevertheless, few efforts have been made to elucidate neural network models for geospatial phenomena while considering their geographic context (Jin 2022, Xing and Sieber 2023), despite the critical role of geographic context in understanding spatial variations and their underlying mechanisms.

To fill these research gaps, this study proposed the application of a long short-term memory (LSTM) model to predict individual residential mobility patterns in the contiguous United States between 2012 and 2019. It leveraged a unique dataset, the DataAxle Historical Consumer Database, which captured long-term migration behavior of a substantial sample of US households. From this data set, the research identified four categories of residential mobility—no move, intra-county move, intra-state move, inter-state move—and predicted the sequence of residential movements over seven years.

The study also employed the geographically localized interpretable model-agnostic explanation (GLIME) to evaluate the model's local fidelity and to enhance explainability. The model-agnostic approach, coupled with geographically localized explanations, enabled the identification of the contributing factors that influenced mobility decisions in different regions. By venturing into the realm of deep neural network models for individual residential mobility data, the study enriches the literature by providing more accurate predictions than traditional regression models over large spatial and temporal extents. Moreover, the research enhances the interpretability of deep learning models, providing insights to the socioeconomic factors that underlie residential mobility at the individual level.

The rest of this article is structured as follows. Section 2 provides background on this research regarding terms of residential mobility in the United States. Section 3 describes our model with evaluation strategies and introduces GLIME. We also explain how we constructed and validated the dataset. Sections 4 and 5 present the findings and concluding remarks, respectively.

## 2. Background

AI-based research has focused on macroscopic predictions of human migration using data on inter-county migration (Robinson and Dilkina 2018), international migration (Golenvaux *et al.* 2020), and job mobility (Xu *et al.* 2019). Employing artificial neural networks (ANNs), these models incorporated input variables representing socioeconomic and environmental characteristics of neighborhoods, such as land use, population density, and economic indicators like median income and Gross Domestic Product, either at the origin or destination. By capturing nonlinear and irregular migration distributions, these ANNs outperform traditional spatial interaction models, such as gravity and radiation models (Alis *et al.* 2021). Macroscopic approaches may suffer from an ecological fallacy, limiting the translation of findings into practical policy and commercial strategies. For example, relying solely on flows between geographically proximate or similar neighborhoods provides only limited insights into how the selective residential mobility of individuals contributes to segregation within a city. Considering that an individual's relocation decision is influenced by neighborhood factors and their own residential history (Schelling 1969, Stovel and Bolan 2004, van Ham and Feijten 2008, Clark and Coulter 2015), investigating residential mobility at multiple levels and encompassing individual-level dynamics becomes essential.

The scant attention provided to individual-level residential mobility dynamics poses a sharp contrast to the significant amount of work on mobility prediction models (Tarasyev *et al.* 2018, Haddad and Sanders 2020, Nurhaida *et al.* 2020, Ip *et al.* 2021, Zhu *et al.* 2022). Despite their relevance to mobility in general, studies on small spatial and temporal scales do not directly address the nuances of residential mobility.

The extensive body of literature on residential mobility offers valuable insights for formulating model specifications to predict individual residential mobility. Classical theories posit that people move or desire to move to adapt to changing life course needs and preferences, including demographic and employment-related events (Rossi 1955, Geist and McManus 2008, Coulter and Scott 2015). For example, young adults often migrate to take advantage of educational and job opportunities elsewhere (Bailey 1993), while parents of young children may relocate in search of more spacious homes (Lee *et al.* 1994). The residential mobility of older adults is influenced by factors such as amenities, a lower cost of living, and their own care needs (Meyer and Cromley 1989, Sergeant and Ekerdt 2008).

The literature has increasingly recognized the significance of neighborhood factors in residential relocations (van Ham and Feijten 2008, Rabe and Taylor 2010, Sharkey and Sampson 2010, Clark and Coulter 2015), though empirical studies have yielded mixed results. Some studies report that distressed neighborhoods, inhabited by low-income residents, rented housing, and ethnic minorities, tend to push residents to move away, with those possessing sufficient socioeconomic capacity opting for better neighborhoods (South and Crowder 1997a, Bailey and Livingston 2008, Rabe and Taylor 2010). In contrast, other studies found that neighborhood characteristics had only a marginal influence on residents' relocation decisions (Clark and Huang 2003, Kearns and Parkes 2003, Clark and Ledwith 2006), suggesting that people's dissatisfaction with their neighborhood might not cause them to move out.

While previous research has often distinguished local from long-distance moves (e.g., across state boundaries), it is increasingly acknowledged that such categorizations may be oversimplifications, as residential moves are rarely driven by a single identifiable motive (Clark 2005, Coulter and Scott 2015). Changes in family life and personal values call for a comprehensive examination of diverse residential trajectories influenced by complex factors (Coulter *et al.* 2016). For instance, long-distance moves may be influenced by individual characteristics interacting with statewide policies and macroeconomic dynamics (Stoll 2013, Johnson *et al.* 2016, Li *et al.* 2020). Moreover, past mobility experiences and path dependence significantly influence future mobility decisions by shaping attachment to a place and willingness to pay for relocation (Bailey 1993, Hassler *et al.* 2005, Orvin and Fatmi 2022).

Methodologically, in the residential mobility literature, earlier empirical studies have predominantly employed traditional logistic and linear regression models. These studies demonstrated the statistical significance of specific variables or groups, rather than achieving high prediction accuracy, resulting in relatively poor model fits. For instance, in Crowder and South's study (2008) that estimated the distance of residential mobility using an Ordinary Least Squares (OLS) model, the adjusted $R^2$ value was 0.024. Similarly, in the work of Robinson and Dilkina (2018) that estimated migration volume between counties using a radiation model, the adjusted $R^2$ value was 0.26.

## 3. Methodology

### 3.1. Recurrent neural networks and long short-term memory

Due to their looping structure, recurrent neural networks (RNNs) are well suited to handle sequential data such as speech processing and non-Markovian control (Hochreiter and Schmidhuber 1997). The network creates hidden neurons representing the current state ($h_t$) with inputs and previous states ($h_{t-1}$) through an activation function (Eq. 1) to encompass the impact of prior results on the current status. The structure enables the identification of the time-variant effects of given covariates, thus fully recurrent neural networks generate a hidden layer that recurrently influences the status of the next steps (Rumelhart *et al.* 1986). With this recurrent structure, a network is able to model temporally autocorrelated events, such as cumulative changes and sequential movements, known as trajectories (C. Wang *et al.* 2022).

$$h_t = f(h_{t-1}, x_t) \tag{1}$$

LSTM models, special RNN architectures, are suggested to limit the risks of vanishing gradient problems in training long-term sequence data (Nair and Hinton 2010). LSTM models enable better learning of long-term dependencies by including more complicated structures of weights in hidden layers that control the way information is stored, forgotten, and utilized throughout training procedures. In an LSTM cell of a hidden layer, four gates determine forgettable information (forget gate, $f_t$ in Eq. 2a), acceptable information (input gate, $i_t$ in Eq. 2b), output information (output gate, $o_t$ in Eq. 2c), and current cell status (cell state, $\tilde{C}_t$ in Eq. 2d) (Hochreiter and Schmidhuber 1997).

$$f_t = \sigma W_f[h_{t-1}, x_t] + b_f) \tag{2a}$$

$$i_t = \sigma W_i[h_{t-1}, x_t] + b_i) \tag{2b}$$

$$o_t = \sigma W_o[h_{t-1}, x_t] + b_o) \tag{2c}$$

$$\tilde{C}_t = \tanh W_C[h_{t-1}, x_t] + b_C) \tag{2d}$$

*W* and *b* with each notation indicate weights and bias. Therefore, the number of trainable weights is $4(nm + n^2)$, where *n* indicates the number of input features, and *m* is the number of output features. The status in an LSTM cell is a function of forgettable information about previous status, acceptable information of current input

(Eq. 3a), and the output of the hidden layer defined as Eq. (1) is determined by the value of the output gate and the activated current state (Eq. 3b).

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{3a}$$

$$h_t = o_t * \tanh(C_t) \tag{3b}$$

As sequential movements are affected not only by recent status but also by historical contexts, LSTM is appropriate for predicting long-term changes. In terms of residential mobility, people's decision to relocate relies both on the previous year's status and on cumulative changes in socioeconomic factors such as income or changes in neighborhood environments. To predict residential mobility for the next year, we built a general two-layered LSTM. Two layers were selected to balance the model's performance and explainability as we tested a new interpreter for the deep learning model. We trained the model with the input features from 2012 to 2018 and with the observed movement types spanning from 2013 to 2019 as output. For the experiments, we trained the model with 70% data and tested it with 30%.

For the evaluation of the model, we selected the model accuracy on the test set, prediction precision, recall rate, F1 score, and balanced accuracy score. After calculating global accuracy, we calculated the local accuracy of the LSTM model through resampling datasets at the state level. Local accuracy compares the goodness-of-fit in local samples to that of the global model. Areas with low accuracy imply that the LSTM model does not fit well in that area with the same input datasets. The loss function measures the distance between the predicted and desired output during training. We chose the categorical cross-entropy loss function for the four types of residential movement as our loss function (Eq. 4).

$$\text{Loss} = -\sum_{i=1}^{4} y_i \log \hat{y}_i \tag{4}$$

We used the F1 score and balanced accuracy to evaluate the performance of the models (Yang and Liu 1999, Brodersen *et al.* 2010) (Eqs. 5a, 5b). This approach is well suited to classification problems with imbalanced data. The precision value of a class ($k$) is the proportion of true positive classification (TP) to the total number of true records classified as class $k$ (Eq. 5c), while the recall value is the proportion of TP to the total number of predictions classified as class $k$ (Eq. 5d). The precision value ranges from 0 to 1, with higher values indicating greater prediction accuracy.

$$F1_k = 2\,\frac{\text{precision}_k \cdot \text{recall}_k}{\text{precision}_k + \text{recall}_k} \tag{5a}$$

$$\text{Balanced Accuracy}_k = \frac{\sum_{k=1}^{K} \text{recall}_k}{K} \tag{5b}$$

$$\text{precision}_k = \frac{TP_k}{TP_k + FP_k} \tag{5c}$$

$$\text{recall}_k = \frac{TP_k}{TP_k + FN_k} \tag{5d}$$

### 3.2. Geographically localized interpretable model-agnostic explanation

We inspected the input features that drove the output of the model by adopting a model agnostic XAI approach. We conducted a sensitivity analysis to explain the relationship between input variables and output classification through the geographically localized interpretable model-agnostic explanation (GLIME), which is a spatially explicit algorithm of the local interpretable model-agnostic explanation (LIME).

The LIME algorithm explains the predictions of a machine learning model, $f(x)$, by approximating it with a local model, $g(x)$, at a data point $x$ and local samples around $x$, following the equation (Ribeiro *et al.* 2016):

$$\xi(x) = \text{argmin } \mathcal{L}(f,\ g,\ \pi_x) + \Omega(g) \tag{7}$$

where $\xi$ is the LIME explanation, $\mathcal{L}$ is the fidelity function, $\pi_x$ is the proximity measure defining locally around a data point $x$, and $\Omega$ is the complexity measure (Patil *et al.* 2019). To ensure interpretability and local fidelity, it is necessary to minimize $\mathcal{L}(f,\ g,\ \pi_x)$ :

$$\mathcal{L}(f,\ g, \pi_x) = \sum_{z, z' \in Z} \pi_x(z)(f(z) - g(z'))^2 \tag{8}$$

where $z$ is a perturbed data point in original data space, and $\pi_x(z)$ is local weights on data points $z$ around data point $x$. In other words, LIME is the value of a loss that minimizes differences between local and global models at a single point with a certain number of data points neighboring the point to be explained. Figure 1a shows the algorithm of LIME (original image from Ribeiro *et al.* 2016). Consider the curve in Figure 1 to be a complex function that categorizes two objects: crosses (+) and circles (•). With the non-linear classifier, it is difficult to explain the relationship between inputs and outputs. However, by focusing on a single observation, a simpler function like a linear regression (i.e., a dashed line in Figure 1a) may be an approximate fit to the complex model. With a reasonable number of neighboring samples, the simple model enables explanations for the relationships between inputs and outputs at the point (highlighted by larger size of crosses and circles in Figure 1a).

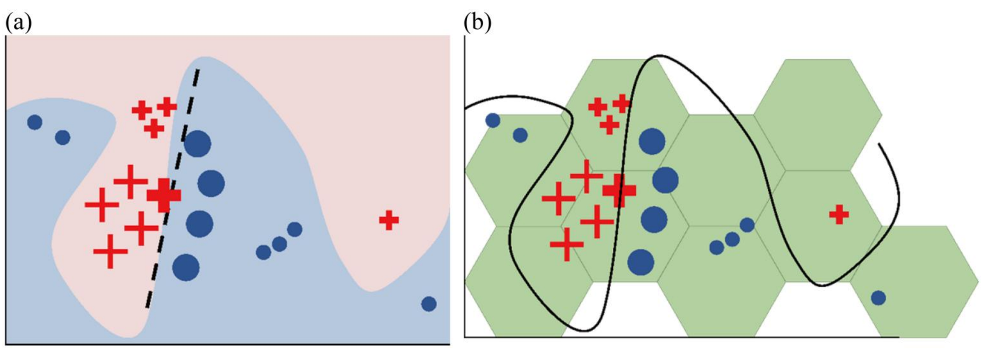


**Figure 1.** Conceptual diagrams for two model-agnostic explanation algorithms: (a) LIME (Ribeiro *et al.* 2016) and (b) GLIME.

Despite its widespread application, LIME has limitations when used for geospatial analysis. The use of conceptual mathematical coordinate systems for neighboring points hinders spatial interpretability. Additionally, arbitrary neighborhood ranges in variable space and sensitivity to the number of neighborhoods can lead to overfitting issues. Furthermore, the local samples chosen lack meaningful spatial implications as they are merely results of model optimization.

To overcome the limitations of LIME in geospatial analysis, we introduce the geographically localized interpretable model-agnostic explanations (GLIME) method. Unlike LIME, GLIME defines local neighborhoods based on geographic units, incorporating human understanding rather than relying solely on model optimization (Figure 1b). By fixing a specific geographic range (e.g., green hexagons in Figure 1b), GLIME is calculated as follows (Jin 2022):

$$\mathcal{L}_{\pi_x}(f,\ g) = \ (f(z) - g(z'))^2 \tag{9}$$

As the neighborhood is given, $\pi_x(z)$ is set such as the census unit or geographic unit. In other words, the fidelity function, $\mathcal{L}$, is localized at $\pi_x(z)$ scale. As depicted in Figure 1b, instead of approximating a simpler local model, GLIME advocates for segmenting the complex model based on geographic units, particularly when the model deals with geospatial events or phenomena affected by characteristics like spatial dependence and heterogeneity. By doing so, GLIME significantly enhances the spatial interpretability of neural network models. It evaluates local fidelities through comparisons to the global model, using well-known geographic units such as states and counties as reference points. This approach sheds light on the intricate spatial relationships between input features and model predictions.

We conducted a comprehensive evaluation of the locally varied impacts of each input variable group by perturbing the model. Intentionally perturbing the inputs serves as a post-hoc model-agnostic approach to test the sensitivity of the model. For instance, if the classification accuracy significantly decreases when a particular input feature decreases, compared to other features, it indicates that said feature holds greater importance for the model. Applying this indirect approach enabled us to understand the relative impacts of input variables. Building upon GLIME's ability to provide a geographic local framework for interpreting complex models, we extended the sensitivity test to GLIME. By doing so, we identified the different local impacts of input features in a spatially explicit manner, enhancing our understanding of how the model responds to changes in specific input variables.

## 4. Data

The data used in this study contained trajectories of 1,126,678 households in the US from 2012 to 2019. The LSTM model was trained to predict the mobility type based on a multivariate time series dataset of 18 factors grouped into five categories. The dataset comprised various attributes, including move history, categorized into four types (represented as dummy variables), six neighborhood factors, a state-related factor accounting for 50 states (represented as a dummy variable), 10 individual factors,

**Table 1.** Descriptive statistics of factors by movement type in 2012.

| | | Descriptive statistics (mean value (standard deviation)) | | | |
|---|---|---|---|---|---|
| Group | Variable | No move | Intra-county | Inter-county | Inter-state |
| Movement History | Movement in the previous year (2011) | No move: 912,714 | No move: 62,429 | No move: 27,131 | No move: 20,873 |
| | | Intra-county: 46,703 | Intra-county: 6,315 | Intra-county: 1,513 | Intra-county: 1,197 |
| | | Inter-county: 21,541 | Inter-county: 2,063 | Inter-county: 2,309 | Inter-county: 673 |
| | | Inter-state: 15,956 | Inter-state: 2,422 | Inter-state: 1,108 | Inter-state: 1,731 |
| Neighborhood | Population density | 4,320.8 (10,821.7) | 5,261.2 (13,424.5) | 5,029.6 (12,630.7) | 4,948.7 (12,814) |
| | % White population | 78.8 (20.3) | 76.9 (21.2) | 77.7 (20.2) | 78.5 (18.4) |
| | % African American population | 10.1 (17) | 11.4 (18.3) | 10.3 (16.4) | 10.2 (15.2) |
| | % families with children | 33.6 (11.4) | 32.5 (11.9) | 32.5 (11.8) | 33.0 (13.4) |
| | Median household income | 66,778.0 (29,794.0) | 61,250.7 (28,028.9) | 63,578.3 (27,118.9) | 68,146.4 (29,291.7) |
| | % Renter Occupied | 29.2 (19.7) | 34.7 (22.0) | 33.4 (22.1) | 33.8 (23.3) |
| State | State (Top 4) | CA: 93,313 | CA: 7,687 | CA: 3,312 | CA: 1,674 |
| | | FL: 70,701 | FL: 5,802 | TX: 3,050 | FL: 1,645 |
| | | TX: 69,235 | TX: 5,660 | FL: 2,137 | TX: 1,463 |
| | | NY: 56,643 | NY: 3,888 | VA: 1,417 | NY: 1,265 |
| Individual | Primary family | Yes: 907,192 | Yes: 62,464 | Yes: 27,059 | Yes: 21,121 |
| | | No: 89,722 | No: 10,765 | No: 5,002 | No: 3,353 |
| | Age of household head | 52.6 (15.7) | 46.8 (15.5) | 46.2 (15.4) | 45.9 (15.3) |
| | Length of residence | 11.8 (10.4) | 8.2 (8.8) | 8.0 (8.8) | 7.1 (7.8) |
| | Marriage status | 5.4 (2.7) | 4.8 (2.7) | 4.9 (2.6) | 5.3 (2.7) |
| | # of children | 0.4 (0.8) | 0.4 (0.8) | 0.3 (0.7) | 0.4 (0.8) |
| | Household wealth | 2,316.0 (786.3) | 1,898.8 (778.2) | 1,948.1 (766.8) | 2,101.4 (815.7) |
| | Household income | 98.7 (76.7) | 79.3 (67.5) | 82.4 (66.8) | 96 (75.9) |
| | Purchasing power | 92.9 (72.5) | 75.2 (64.1) | 78.4 (63.6) | 91.4 (72.9) |
| | Housing tenure | 7.7 (2.2) | 6.3 (2.7) | 6.4 (2.7) | 6.7 (2.7) |
| | Home value | 244.2 (268) | 193.4 (249.3) | 197.1 (249.5) | 228.4 (261.1) |
| Housing type | Housing type (Top 4) | SFDU: 874,655 | SFDU: 54,724 | SFDU: 24,313 | SFDU: 19,283 |
| | | MFDU: 114,063 | MFDU: 17,678 | MFDU: 7,497 | MFDU: 5,002 |
| | | Trailer: 4,528 | Trailer: 493 | Trailer: 167 | Trailer: 115 |
| | | Retire: 3,148 | Retire: 281 | Retire: 69 | Retire: 58 |
| | Obs. | 996,914 | 73,229 | 32,061 | 24,474 |

Household wealth (between 0 and 9999), income (5-500), purchasing power (5-500), and home value (5-9999) are estimated values in thousands of US dollars.
Housing tenure indicates likelihood that the household either owns their home or is renting using the score ranging from 0 and 9. The higher the score, the more likely to own the home.
Marriage status is a score that estimates the likelihood that the head of household is married (0-9). The higher the value, the more likely to be married.
Four factors, state, primary family, movement in the previous year, and housing type, were included in the model as dummy variables.

and one housing status-related factor with six types (also represented as dummy variables). All of these attributes were recorded on an annual basis (Table 1).

The residential mobility trajectories of households and their associated socioeconomic variables were provided by the Data Axle Historical Consumer Database. The database contains the socioeconomic status and residential address of households, tracked by a unique identification number (household ID) with variables captured annually for 155 million households in the US (Data Axle 2021). While the data is constructed for business use (e.g., advertising campaigns), academic researchers have used it to examine residential mobility in relation to neighborhood change (Greenlee 2019), neighborhood type (Pan *et al.* 2020), location preferences (Wang *et al.* 2021), and land cover change (Park *et al.* 2022). It covers a large sample of individual households (i.e., 15.4% of undercoverage rate, Kennel and Li 2009) with address information at a finer scale and is much less vulnerable to selection bias.

In this study, we compiled a longitudinal dataset comprising 60,773,935 households continuously present from 2012 to 2019. Among these households, 10,971,745 experienced at least one relocation during the 7-year period. The dataset exhibited class imbalance, with a significant proportion of households maintaining the same address over time, while long-distance moves were more infrequent than short-distance moves (Cadwallader 1992, Kaplan and Schulhofer-wohl 2017).

To rectify the class imbalance, which can adversely affect deep learning models, we employed random undersampling (Estabrooks and Japkowicz 2001, Mohammed *et al.* 2020). This technique randomly eliminates instances from the majority class. Specifically, we sampled 281,688 households based on the number that moved from one state to another between 2018 and 2019. Subsequently, we randomly selected an equal number of instances for the other three classes. To ensure data integrity, households with missing values were removed from the dataset. As a result, we obtained a balanced dataset containing 1,126,678 households and 7,886,746 observations (1,126,678 households x 7 years) to be used in our model.

From the Data Axle Database, we selected ten factors that capture individual household characteristics and reflect changes in their life course. These factors were primary family (yes: 1, no: 0), age of household head, length of residence, number of children, household wealth, household income, housing tenure, home value, marriage status, and purchasing power. To account for move history, we introduced a dummy variable representing movement types in the previous year: no move, intra-county move, inter-county move, and inter-state move. Additionally, housing type was incorporated as a dummy variable, encompassing different kinds of physical structures: Multiple Family Dwelling Unit (MFDU), Single Family Dwelling Unit (SFDU), nursing home, and retirement home. While some variables were estimated rather than directly reported, they were found to be strongly correlated with the American Community Survey (ACS) data at the census tract level (Park *et al.* 2022).

We retrieved neighborhood factors from the American Community Survey (ACS) 5-year estimates for each year, ranging from ACS 2008-2012 to ACS 2014-2018, based on the address information before households made the decision to move. The selected neighborhood factors were population density, the proportion of the white population, the proportion of the African American population, the proportion of families with children, median household income, and median rent. These factors allowed us to examine the influence of socioeconomic characteristics at the census tract level on household relocations. To account for variations in policy environments across different states such as housing provision and tax policies, we incorporated dummy variables representing each state. All continuous variables were standardized using z-scores to ensure a consistent scale for comparison.

## 5. Results and discussions

### 5.1. Model specification

We built the LSTM model with two hidden layers of LSTM and a fully connected layer to predict four types of residential movement for each year. The LSTM model has 75 input variables[1] over seven years from 2012 to 2018 (i.e., input size = # of samples * 7 * 75) and output classes over seven years from 2013 to 2019 (i.e., output size = # of sample * 7 * 4). In the two LSTM layers, we set the hidden units to 64 to facilitate calculation efficiency, so the number of parameters for each hidden layer is 35,584 ($4*(75*64+64^2)$) and 32,768 ($4*(64*64+64^2)$). We also set the dropout regularization with a dropout rate of 20% between LSTM layers to reduce overfitting and to ensure a better generalization. At the final layer, a fully connected layer, the sigmoid function was used as an activation function that synthesizes all information passing through LSTM layers. With a learning rate of 0.01, the model was trained on 70% of the data (788,674 observations) until the accuracy was no longer improved using an early-stop method that reduced computational burdens. Although there was a risk that the model would be stuck in local optima, the method enabled feasible computation. The model produced the optimum outputs in 28 iterations (i.e., 28 epochs). Training time was approximately 200 seconds per epoch with our chosen CPU (Intel Core i5-1135G7) and 16GB RAM, rather than GPU. An RNN model and multinomial logistic regression model were developed for comparison.

### 5.2. Model evaluation

From the model-loss graph of the LSTM model, the train losses were reduced at the first few epochs but increased slightly at the end of epochs (Figure 2a). As we chose the early stopping method to avoid model inefficiency, the model stopped its iteration when the loss keeps increasing. The validation losses were more stable than train losses over epochs, which implies that the model is successfully handling overfitting. The model-accuracy graph (Figure 2b) shows that both the training and validation accuracies were close to 80% at the end of training while being stable over epochs. The stability observed stemmed largely from the nature of classification problems. For instance, when a model predicted movement types with probabilities of 0.6 and 0.9, the calculation of loss values differed for these two predictions. However, accuracy, being a binary measure of correctness, treated both cases equally. In both scenarios, where the probabilities exceeded 0.5, they were classified as accurate predictions.

The non-normalized confusion matrix in Tables 2–4 gives the actual number of correctly and incorrectly classified cases for the four types of residential mobility. The

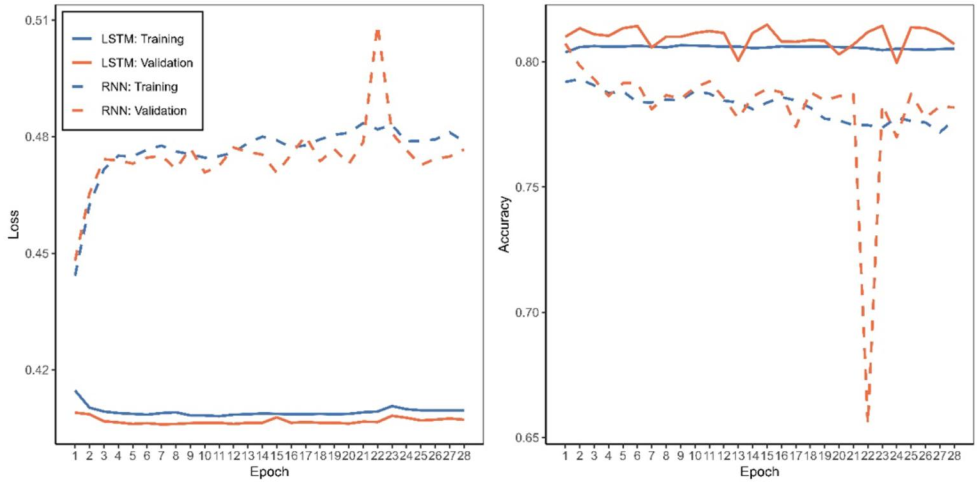


**Figure 2.** The performance comparison of the LSTM and RNN on the test and validation sets: loss (left) and accuracy (right).

**Table 2.** Confusion matrix of the LSTM model.

| True \| Pred | No move | Intra-county | Inter-county | Inter-state | Total |
|---|---|---|---|---|---|
| No move | 6,180,989 | 10,525 | 12,775 | 10,972 | 6,215,261 |
| Intra-county | 508,855 | 79,878 | 76,907 | 43,307 | 708,947 |
| Inter-county | 290,504 | 39,629 | 125,413 | 44,534 | 500,080 |
| Inter-state | 257,675 | 34,187 | 83,228 | 87,368 | 462,458 |
| Total | 7,238,023 | 164,219 | 298,323 | 186,181 | 7,886,746 |
| Precision | 0.85 | 0.49 | 0.42 | 0.47 | 0.56 |
| Recall | 0.99 | 0.11 | 0.25 | 0.19 | 0.39 |
| F1 Score | 0.92 | 0.18 | 0.31 | 0.27 | 0.42 |
| Accuracy | | | | | 0.821 |
| Balanced Accuracy | | | | | 0.387 |

The grey shade values indicate the number of correctly classified objects by the model.

**Table 3.** Confusion matrix of the RNN model.

| True \| Pred | No move | Intra-county | Inter-county | Inter-state | Total |
|---|---|---|---|---|---|
| No move | 6,007,451 | 30,124 | 7622 | 170,064 | 6,215,261 |
| Intra-county | 562,022 | 14,655 | 2095 | 130,175 | 708,947 |
| Inter-county | 350,258 | 12,125 | 1720 | 135,977 | 500,080 |
| Inter-state | 306,039 | 11,220 | 1524 | 143,675 | 462,458 |
| Total | 7,225,770 | 68,124 | 12,961 | 579,891 | 7,886,746 |
| Precision | 0.83 | 0.22 | 0.13 | 0.25 | 0.36 |
| Recall | 0.97 | 0.02 | 0.00 | 0.31 | 0.33 |
| F1 Score | 0.89 | 0.04 | 0.01 | 0.28 | 0.31 |
| Accuracy | | | | | 0.782 |
| Balanced Accuracy | | | | | 0.325 |

The grey shade values indicate the number of correctly classified objects by the model.

LSTM model, employed to classify residential mobility patterns, demonstrated superior predictive performance with an accuracy of 82.1%, outperforming the RNN model with 78.2% accuracy. In contrast, the multinomial logistic regression model exhibited the lowest balanced accuracy of 25%, as it overwhelmingly classified 99.9% of all residents

**Table 4.** Confusion matrix of the multinomial logistic regression model.

| True ∣ Pred | No move | Intra-county | Inter-county | Inter-state | Total |
|---|---|---|---|---|---|
| No move | 6,213,984 | 906 | 259 | 112 | 6,215,261 |
| Intra-county | 708,161 | 706 | 65 | 15 | 708,947 |
| Inter-county | 499,757 | 177 | 142 | 4 | 500,080 |
| Inter-state | 462,207 | 193 | 19 | 39 | 462,458 |
| Total | 7,884,109 | 1982 | 485 | 170 | 7,886,746 |
| Precision | 1.00 | 0.00 | 0.00 | 0.00 | 0.25 |
| Recall | 0.79 | 0.34 | 0.31 | 0.21 | 0.41 |
| F1 Score | 0.88 | 0.00 | 0.00 | 0.00 | 0.22 |
| Accuracy | | | | | 0.788 |
| Balanced Accuracy | | | | | 0.250 |

The grey shade values indicate the number of correctly classified objects by the model.

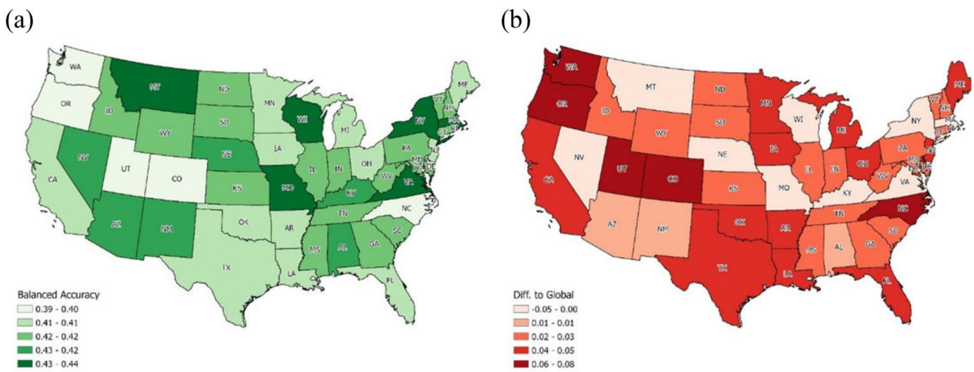


**Figure 3.** (a) Local balanced accuracy by state and (b) local differences to global balanced accuracy by state.

as "no move" type in Table 4. The balanced accuracy value was comparable to a random guess.

The RNN model's lower accuracy arose from its inability to predict intra- and inter-county moves and overestimation of "no move" and inter-state moves. The LSTM model showed improved performance with precision for all classes being two times higher than those of the RNN except for the "no move" type. Although the precisions for the three types of moves (other than "no move") did not reach the desired levels, the LSTM model excelled in distinguishing moves based on distance. For instance, a significant proportion of inter-state moves were misclassified as inter-county moves, and false negative cases of intra-county moves were more commonly misclassified as inter-county rather than inter-state moves.

### 5.3. Interpretation of LSTM model through GLIME

With the aid of GLIME, which uses a geographical framework, we interpreted the LSTM model predicting residential mobility at the state level. This interpretation became accessible when the overarching complex model was partitioned based on geographical neighborhoods, such as states. Figure 3a presents the spatial distributions of local balanced accuracy at the state level. The Mideast and Northeast regions of the United States exhibited higher accuracy than the West and Southwest regions. The areas characterized by higher accuracy suggested that residential movement patterns can be more reliably predicted using the provided input datasets which have been constructed based on insights from the residential mobility literature, emphasizing the influence of neighborhood and individual factors.

However, certain regions in the Western United States displayed lower accuracy, indicating that these areas were less predictable using the given datasets. A similar spatial pattern of contrast between the western and (mid)eastern regions was also evident

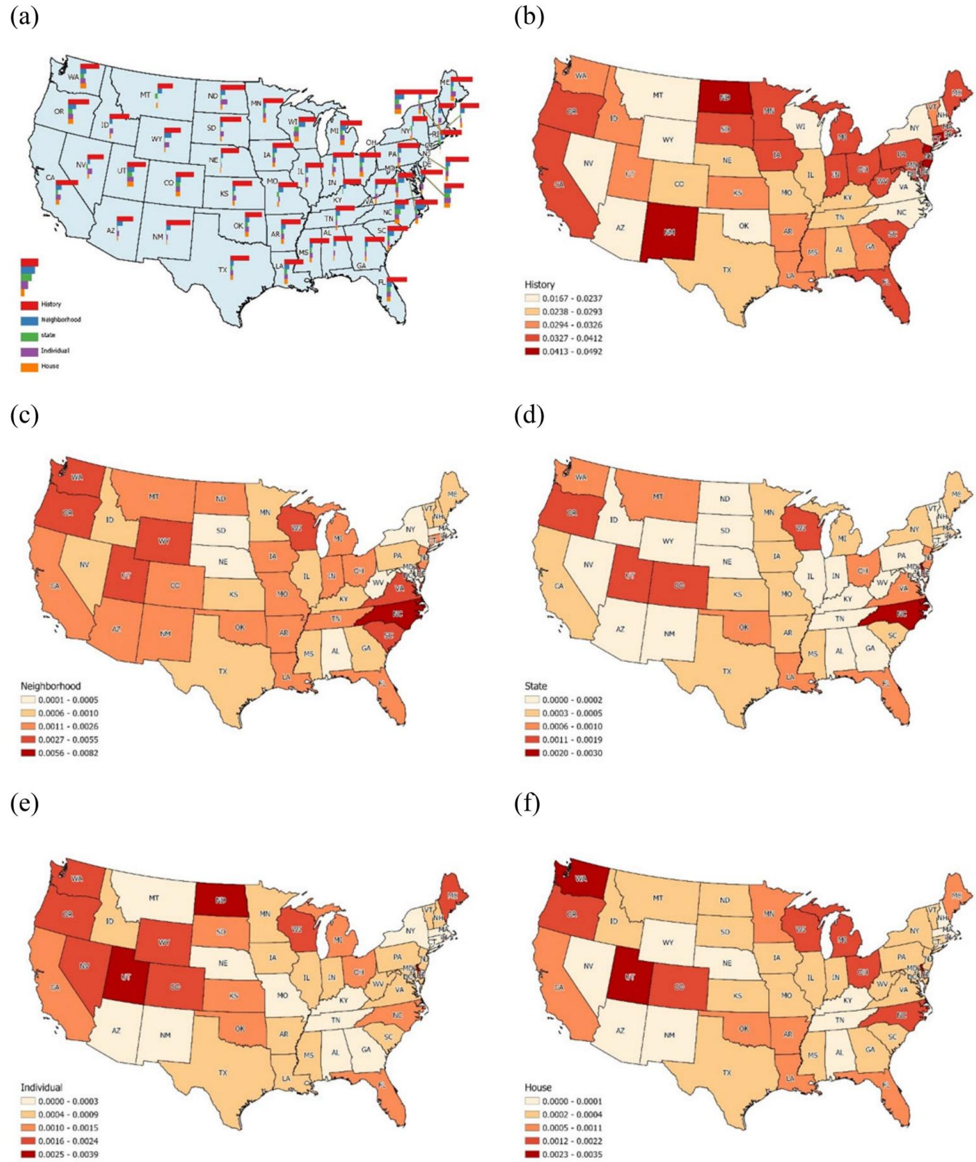


**Figure 4.** Local impacts of variable groups at state level: (a) relative importance of variable groups in each state; (b) history; (c) neighborhood; (d) state; (e) individual; and (f) house type.

in the work of Robinson and Dilkina (2018), where they estimated county-to-county residential mobility using an ANN model. This consistent spatial pattern suggests that our model encountered challenges in comprehensively capturing the intricate dynamics of residential mobility within those geographic areas. For instance, the presence of a growing Hispanic and Latino American population in the South and West could lead to a variety of decisions concerning their new places of residence (Parisi *et al.* 2019). Certain states exhibiting positive net-migration trends, such as North Carolina, Oregon, Utah, Texas, and Florida, where population growth results from inter-state moves and international migration, displayed noteworthy deviations in balanced accuracy from the national average (U.S. Census Bureau 2023) (Figure 3b).

Figure 4 presents the relative importance of input variable groups and their impact on the model at state level. Through the perturbation of model input variables by group, we quantified the importance of these variables. The history of moves emerged as a major determinant with considerable influence on the model's predictive outcomes. The observation is depicted by the dominant red bars in Figure 4a, which represent the highest importance scores across all states. This finding underscores the significance of path dependence as a robust driver of move decisions (Hassler *et al.* 2005). Most people without prior experience of relocating tend to favor staying in their current residence. While previous studies employing conventional statistical models indicated that the length of residence, serving as a proxy for path dependency, influenced future behaviors (Bailey 1993, Hassler *et al.* 2005, Orvin and Fatmi 2022), our LSTM model, empowered by longitudinal data, revealed that past residential mobility had a significant impact on future mobility patterns through the learning of temporal dependencies.

The neighborhood variable group and state factor exhibited more pronounced effects than the individual- and house-type factors. The outcome diverged from previous research suggesting that residents' dissatisfaction with their neighborhood was less likely to prompt actual moves (Clark and Huang 2003, Clark and Ledwith 2006). Several reasons underlie this discrepancy, warranting further investigation. First, our findings align with the proposition that dissatisfaction with neighborhoods is a motivating factor for residents to seek alternatives (Kearns and Parkes 2003, Bailey and Livingston 2008). Factors related to neighborhood quality, amenities, or social dynamics might prompt them to consider moving to more desirable locations. Second, the influence of spatial factors becomes more prominent when individual move history is considered separately from individual-specific factors. Additionally, geographical considerations such as proximity to workplaces, availability of essential services, or access to recreational facilities, are likewise pivotal in shaping decisions on residential movements, alongside neighborhood characteristics that our model considered. Third, the relatively short (7-year) duration of the longitudinal data might limit its ability to reflect individuals' complete life cycles and long-term mobility motivations. Consequently, individual motivations for relocation within the timeframe could potentially be underestimated, as factors influencing more extended periods of residence are not fully captured.

The results indicate that local effects of variables are geographically heterogeneous. An examination of North Carolina and Delaware revealed that the effects of neighborhood and state variables appeared more pronounced in these states than in others. This suggests that North Carolina and Delaware residents are attuned to the characteristics of their immediate neighborhood environment and the statewide policies that govern residential mobility decisions. These distinctive patterns of influence may be linked to the varying policy frameworks across states. Diverse state-level policies, encompassing matters such as statewide tax incentives, housing affordability programs, or urban development initiatives, potentially contribute to the divergent impact of state factors on residential mobility determinations. State-level policies and programs can significantly shape the attractiveness of specific neighborhoods or regions (Stoll 2013, Bell Policy Center 2018, Li *et al.* 2020), consequently influencing the relocation choices of potential movers and amplifying the spatial heterogeneity observed in the patterns of influence.

In contrast, the states of Utah, North Dakota, and Washington demonstrated stronger impacts of individual factors, including individual characteristics and housing types. This distinction suggests that residents in these states are more influenced by their personal attributes and housing preferences when making decisions about residential moves. These states may have populations with unique preferences and priorities when it comes to housing and lifestyle choices. For instance, Utah has a younger population and a significant number of families, which may influence the importance of individual and housing-related factors in their relocation decisions.

## 6. Conclusions

Our research has showcased the effectiveness of deep neural models and the significance of the GLIME approach in understanding complex geospatial processes, which play a crucial role in decision-making within our society. By applying the GLIME approach to a two-layered LSTM model, we explored the applicability of explainable deep learning techniques to human mobility over larger spatial and temporal extents, focusing on individual-level residential mobility patterns across the United States from 2012 to 2019. The LSTM model outperformed the traditional multinomial logistic regression model and the RNN model regarding balanced accuracy for the imbalanced dataset. Moreover, GLIME enabled spatially explicit interpretations and evaluated local impacts that generates new hypotheses for future study. Our findings highlighted the importance of considering path dependency of households in understanding residential mobility.

The inherent complexity of human geographic phenomena and social sciences manifests in the unpredictable and irregular patterns characterizing socioeconomic behaviors. While deep neural networks have demonstrated remarkable proficiency in image classification tasks, where patterns are discernible and straightforward, they encounter difficulties in accurately predicting human decision-making processes. This is primarily attributed to the significant uncertainties and outliers prevalent in such data, reflecting the intricate and multifaceted nature of human choices.

Our research represents a pioneering effort in applying deep learning techniques to the analysis of long-term and large-scale human mobility, particularly in the context of residential movements. Such mobility entails a multitude of unplanned and unexpected events, adding to the challenges of modeling. Despite the inherent complexities and uncertainties, there remains room to enhance the performance of the model. With continued refinement of and advances in deep learning methodologies, the potential for improved accuracy and insights into human mobility patterns remains promising.

Moreover, this research introduced a novel approach to geographically interpretable deep learning models. With GLIME, our study allowed for a comprehensive understanding of complex models at specific geographic units, which proved invaluable in the context of geospatial applications of deep learning. However, the significance of the modifiable areal unit problem (MAUP) becomes evident when addressing geographically explainable AI. In our research, movement types were classified based on administrative units, which may not align with practical areal units for certain cases. For instance, the New York metropolitan area spans three states (New York, New Jersey, and Connecticut), and residents may not consider relocation within the region as an inter-state move. Consequently, this study may not fully elucidate the complexities underlying such moves.

In response to the concern, embracing geographical contexts such as metropolitan statistical areas or urban-suburban-rural distinctions has the potential to bolster prediction accuracy and facilitate more comprehensive investigations. Accounting for these spatial delineations will enable a finer-grained analysis of residential mobility patterns, leading to improved model performance and a more nuanced understanding of geospatial dynamics.

While the Data Axle dataset used in this study offers valuable information about individual households, it does have certain limitations. Most variables are estimated and provided as interval values, which can hinder the accurate assessment of their individual impacts on the model. There exists a potential for interdependencies between variables, leading to reduced variance in individual characteristics and potentially underestimating their influence on the model's predictions. Additionally, the absence of racial information is a significant limitation, as race can be an important determinant of residential patterns in the United States. Access to more detailed data, including racial information, would allow for deeper investigations into the effects of individual characteristics on mobility.

By employing geographically explainable deep neural networks, our research has not only improved the prediction of residential mobility but has also shed light on the complex mechanisms underlying this phenomenon. GLIME has proven valuable in enhancing our understanding of the geographical aspects of human mobility. The research contributes to the broader literature on residential mobility by showcasing the potential of combining multiple variables nonlinearly and by advocating for deeper explorations of path dependency and spatial heterogeneities. As we continue to refine our models and access more comprehensive datasets, we can further advance our knowledge of human mobility and its implications for decision-making.

## Note

1. We have 75 variables in total as categorical variables including state and housing type are input as dummy variables into the models.

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## Data and codes availability statement

The data, codes, and instructions that support the findings of this study are available on *figshare* at https://doi.org/10.6084/m9.figshare.21543549.v1

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