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Opportunities and shortcomings of AI for spatial epidemiology and health disparities research on aging and the life course

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A B S T R A C T

Established spatial and life course methods have helped epidemiologists and health and medical geographers study the impact of individual and area-level determinants on health disparities. While these methods are effective, the emergence of Geospatial Artificial Intelligence (GeoAI) offers new opportunities to leverage complex and multi-scalar data in spatial aging and life course research. The objective of this perspective is three-fold: (1) to review established methods in aging, life course, and spatial epidemiology research; (2) to highlight some of the opportunities offered by GeoAI for enhancing research on health disparities across life course and aging research; (3) to discuss the shortcomings of using GeoAI methods in aging and life course studies.

1. Introduction

Interdisciplinary fields such as life course and spatial epidemiology have relied on a variety of traditionally established methods to understand the impact of the built and natural environment on health disparities among diverse populations. Spatial life course epidemiology, an emerging area of science, seeks to investigate the life course effects of environmental factors on individual behaviors and health outcomes at high spatiotemporal resolution, accuracy, and precision (Jia et al., 2019; Pearce et al., 2016). Established methods in these fields have allowed several advances for understanding the impact of spaces and places on health exposures and outcomes. With the increasing use of Artificial Intelligence (AI) methods integrated with geospatial sciences, or GeoAI, we may be able to further advance life course and spatial epidemiology by incorporating GeoAI methods along with traditional methods to address some of the issues faced in these interdisciplinary fields (Janowicz et al., 2020). In this short essay, we first concisely review established methods in spatial epidemiology and how AI, mainly GeoAI, could enhance our understanding of health disparities across aging and life course research. Next, we highlight how to incorporate GeoAI methods in aging and life course studies including the many opportunities and notable limitations. Finally, we provide concluding remarks and suggest avenues for further investigation.

1.1. Established methods

Established methods in aging, life course, and spatial epidemiology generally include long-term observational (e.g., longitudinal), birth cohort, structural equation modeling (SEM), agent-based modeling (ABMs), space-time ecological, and space-time regression studies. Established spatial and life course methods have helped epidemiologists describe and quantify the impact of the built and natural environments on health by allowing the examination of the distribution of adverse exposures, differential impacts of adverse exposures, and their overall contributions to health inequities. This has been accomplished with the methods' three primary attributes: utility, flexibility, and interpretability. First, these methods have been useful in allowing us to incorporate individuals' spatial exposures from multiple environments including individuals' home, work, and school environments. We have made advances in linking individual-level and area-level structural and social determinants via administrative data sources. Second, the flexibility of these methods has allowed for the incorporation of several spatial scales (e.g., zip codes, census tracts, cities, etc.) across social ecological health-related domains (e.g., built environment, education, health care) to examine different health outcomes (e.g. infectious and chronic diseases). Lastly, traditional methods have allowed spatial and life course epidemiologists to readily interpret their findings for public health impact and influencing policy and public health strategies.

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Notable examples include tobacco retail density and proximity with adolescent tobacco use; historical residential segregation and present-day cancer disparities; neighborhood-level air pollution, cardiovascular disease, cognitive outcomes among older adults(Crane et al., 2024; Gao and Wang, 2024; Hirsch et al., 2022; Moored et al., 2022), and COVID-19 (Holuka et al., 2020; Kephart et al., 2021; Letcher et al., 2023; Settersten et al., 2020).

Despite the advancements and strengths of well-established spatial life course methods, they are not designed to handle the need for high-quality multi-scalar data for this type of longitudinal research; computational intensity of data processing, recoding, and analysis; and the sheer volume of potential noise, complexity, and uncertainty of these large spatiotemporal datasets (Delmelle et al., 2022; Desjardins et al., 2023). The advent and recent growth of AI and GeoAI are particularly salient approaches that may mitigate the analytical and computational challenges of conducting high-quality and representative spatial life course research.

2. Incorporating AI methods

2.1. Opportunities

There is a critical need to address these research gaps and shift our science to leverage and generate AI methods specifically for spatial epidemiology. AI can provide the tools to address these gaps by doing what natural intelligence can't – *"everything all at once."* In the context of aging research, AI methods can potentially allow us to *simultaneously* (1) incorporate multilevel and life course influences operating through multiple pathways, (2) examine and disentangle complexities of changing spaces and places, (3) incorporate a life course approach focusing on longitudinal studies and full life spans, (4) incorporate a-priori assumptions while revealing unknown associations for multiple health outcomes, and (5) keep up with the changing health data landscape while providing real-world and timely results.

AI methods provide new possibilities for spatial epidemiology and health disparities research over the life course. Here, AI methods refer to computational approaches that can complete tasks that previously require human intelligence. More specifically, AI methods include machine learning methods, deep learning methods, and other approaches (e.g., rule-based approaches). Machine learning methods refer to more traditional AI models, such as support vector machine and random forest, while deep learning methods refer to deep neural network based AI models, such as convolutional neural network (CNN), recurrent neural networks (RNN), and generative adversarial network (GAN). While there is a lot of support for deep learning methods, existing research has shown that machine learning methods perform better on small and more structured datasets while deep learning methods perform better on large datasets involving images and natural language texts (Gao et al., 2019; Hu et al., 2021). GeoAI adds an additional emphasis on geographic locations which are critical for linking diverse datasets in health research (e.g., linking residential locations to nearby greenspace) (Hu et al., 2019). GeoAI methods also often consider spatial autocorrelation and spatial heterogeneity which commonly exist in geographic data (Li et al., 2021). There are many possible applications of GeoAI in health research (Kamel et al., 2019; VoPham et al., 2018). Aging research specifically represents a significant starting point for using AI in epidemiology. Aging outcomes can be affected by a wide variety of factors, uniquely lending this type of research to the applications of AI. Below, we discuss a number of aspects that AI can contribute to aging research.

- Extracting environmental features difficult to be captured previously. While the living environment is known to be associated with aging outcomes, it was traditionally difficult to capture environment features especially over long time periods. The availability of street view images (e.g., Google Street View and Mapillary) and deep learning models (e.g., CNN) make it possible to extract important environmental features, such as greenness of a neighborhood space, housing conditions, environmental hazards, and important amenities to support urban accessibility and well-being for older adults (e.g., benches, sidewalks, crosswalks, parks, etc.) (Amaya et al., 2022; Ottoni et al., 2016; Rosso et al., 2011). Street view image data are updated periodically, and the extracted environmental features can be stored over time to enable the examination of their long-term effects on aging outcomes (Kang et al., 2020).
- Improving the resolution and accuracy of environmental data. Environmental data used in previous studies may have coarse spatial resolutions and limited accuracy, due to the data collection procedure and the used instruments. For example, images collected by satellites may have a spatial resolution that is too coarse to conduct more precise health modeling, while data collected by air quality sensors may be limited by the locations where these sensors can be installed. Machine learning and deep learning models, such as random forest and RNN, have been used to generate environmental data with higher resolution and higher accuracy, such as PM 2.5 concentration data(Bi et al., 2022; Lin et al., 2017; Tong et al., 2019). These finer and more accurate environmental data may help us better understand the effects of environmental factors on aging outcomes, such as dementia and other cognitive disorders.
- Identifying important predictors for aging outcomes and generating hypotheses. Traditional methods often require a manual selection of a small set of predictors to study their associations with an aging outcome. While such an approach is effective in many cases, manually selecting from a large set of possible predictors (e.g., 100 predictors) is time-consuming and could miss certain important predictors. AI models, combined with recent explainable AI frameworks (e.g., the SHapley Additive exPlanations) can automate the selection and testing of predictors from a large set of candidates to identify the important ones and to further support hypothesis generation. In addition, machine learning and deep learning can help test the importance of new predictors not examined in previous studies for health outcomes. (Lundberg and Lee, 2017; Chang et al., 2022; Zhou et al., 2022). Furthermore, existing vital statistics and health behavior measures are crucial variables for robust predictors of aging (Nguyen et al., 2021; Tian et al., 2023; Wu et al., 2021).
- Providing time-series predictions based on historical data. Life course health research can accumulate long-term data about individuals and their surrounding environments. These long-term historical data allow us to perform time-series predictions for future health outcomes and future environmental conditions. Deep learning, especially RNNs and transformer models, have demonstrated outstanding performance for time-series based prediction tasks (Géron, 2022; Vaswani et al., 2017). Existing research has leveraged deep learning models and personal health data collected from wearable devices to predict health issues (Coutts et al., 2020; Sathyanarayana et al., 2016). This direction also has potential to enhance precision medicine, i.e., to predict potential health issues based on personal health data and to further prescribe treatment based on the identified issues (Denny and Collins, 2021). Other important historical data that can enhance longitudinal analyses is family health history, which are strongly associated with individual health outcomes across the life course, especially among older aged adults (Baldwin et al., 2021; Fadlon and Nielsen, 2019; Umberson and Thomeer, 2020).
- Reconstructing historical exposures by using GeoAI to geoimpute and create harmonized databases of placed-based and individual-level measures of health (Delmelle et al., 2022). Since there has been a recent shift towards more neighborhood-level life course studies, it is critical to accurately link residential histories with archived census-type data sources. However, census tracts did not cover the entire United States until 1990 (for example), creating challenges for spatially explicit life course analyses. Therefore, a

variety of ancillary data sources are required, such as archived paper maps that need to be georeferenced and satellite imagery from the 20th century. GeoAI approaches can be developed to georeference a massive number of maps to facilitate historical address locators for geocoding and classify these maps to geoimpute study populations to habitable areas in the subsequent digital maps. Moreover, advancements in AI technologies, parallel computing, and cloud-based platforms have significantly enhanced the scalability and efficiency of GeoAI solutions, enabling them to process massive amounts of geospatial data in a timely manner. This scalability makes GeoAI well-suited for applications requiring georeferencing, geocoding, and geoimputation across large datasets.

The above five aspects, while exciting, are not exhaustive, and GeoAI methods could contribute to many other aspects in life course spatial epidemiology. When applied to communities in different geographic areas (e.g., different census tracts) or individuals in different demographic groups, GeoAI methods can further contribute to advancing health disparities research. When individual-level health data are involved, additional caution and research steps should be taken to protect privacy, such as carefully following Institutional Review Board (IRB) guidelines or using proper privacy protection algorithms (Wang et al., 2022). In addition, new AI methods and models are being developed constantly, such as the recent large language models like ChatGPT. There are many opportunities to explore new integrations between AI and health research in the coming years (Lin et al., 2017; Tong et al., 2019). It is important to acknowledge that AI and traditional statistics are not mutually exclusive but rather complementary. AI can handle large, complex datasets and uncover patterns that traditional methods might miss, while traditional statistics provide robust, interpretable models. Hybrid approaches can be utilized, where AI is used for initial data processing and pattern recognition, followed by traditional statistical methods for inference and validation. Furthermore, since placed-based and environmental predictors contain bias and uncertainty (Delmelle et al., 2022), AI approaches should incorporate individual health-based measures such as EMR, family health and residential histories, and vital statistics and behavioral measures, as discussed above.

3. Shortcomings

GeoAI's promising opportunities come with a variety of notable limitations. First, AI methods, especially deep learning models, require a large set of representative and labeled datasets for model training. The phrase "garbage in and garbage out" is well known in AI research (Amaya et al., 2022). However, it is often time-consuming and labor-intensive to obtain high-quality labeled training data, especially for life course epidemiology which requires "living laboratory" datasets over populations' full life spans. Meanwhile, this difficulty of obtaining labeled training data may also be alleviated in life course and aging research where we can leverage historical data, i.e., historical health outcomes can be directly used as labeled data for training predictive models. Second, applying modern AI methods to examine health and place also faces challenges arising from model generalizability and spatial heterogeneity. An AI model trained on the geographic data from one spatial area may not necessarily be generalized to another spatial area, though this is an issue with spatial models in general (Hu et al., 2019). Third, engaging AI without active considerations of foundational theories in epidemiology and spatial sciences may lead to a deviation of the fundamental objective of spatial sciences – to understand 'the principles by which the human and environmental worlds operate.' (Hu et al., 2024) This is manifested in many ways including focusing on prediction and data driven exercises and repackaging established traditional methods as GeoAI while only adding spatial variables. Continuing to use AI for prediction in health research perpetuates limited generalizability and slows down discovery of innovative GeoAI approaches to answer important research questions. Fourth, While AI can potentially identify predictors of aging outcomes, the generation of hypotheses remains the domain of human researchers. AI can indeed support hypothesis generation by offering insights that human researchers can further explore and validate. Finally, misuses of geospatial data in AI research pose significant threats to ethical scientific inquiry to address public health issues (Kamel et al., 2022). One notable issue is privacy, especially geoprivacy, in which personal information and sensitive locations are accidently revealed when AI models are not properly used or designed. Recent research has made progress in protecting individual privacy in AI and health research (Rao et al., 2023; Wang and Kwan, 2020). Privacy and other ethical issues will need our further attention when we use AI and GeoAI methods.

Despite these limitations, there is also a fundamental risk in staying within our comfortable zone by using only the same established methods over time for health research. Failing to explore novel AI methods may miss good opportunities to advance spatial epidemiology and can be in of itself a danger that will widen the time gap between science and technology even further beyond the 17-year odyssey (Green et al., 2009). We also encourage researchers to utilize AI techniques to enhance established techniques in spatial optimization, geostatistical prediction, space-time regression, etc. Finally, we acknowledge that the gap between research and improved policies strongly depends on stakeholders and decision-makers that may have differing agendas, limited resources, and lack of scientific expertise. Therefore, researchers in GeoAI should carefully consider approaches to improve communication and policy implications to inform those responsible for implementing evidence-based change.

4. Conclusion

GeoAI offers new opportunities for advancing transdisciplinary spatial and life course epidemiologic research. By focusing on aging and life course epidemiology, this short essay discusses five aspects where AI (especially GeoAI) can make effective contributions: extracting environmental features, improving the resolution and accuracy of environmental data, identifying important health predictors, providing time-series based predictions, and reconstructing historical exposures. These AI-enhanced aspects may help increase our scientific understanding of the complex, bidirectional, and interdependent relationships of the environment and population health during our lifetime. While not without shortcomings, incorporating AI methods into our established scientific frameworks may strengthen our science, advance health equity, and provide significant insights for long-term health.

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Hoda S. Abdel Magid: Writing – review & editing, Writing – original draft, Supervision, Conceptualization. **Michael R. Desjardins:** Writing – original draft, Writing – review & editing, Conceptualization. **Yingjie Hu:** Writing – original draft, Writing – review & editing.

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