societies

MDPI

Article

Using Digital Tools to Understand Global Development Continuums

J. de Curtò [1,2,3,*] and I. de Zarzà [3,4]

[1] Department of Computer Applications in Science & Engineering, BARCELONA Supercomputing Center, 08034 Barcelona, Spain
[2] Escuela Técnica Superior de Ingeniería (ICAI), Universidad Pontificia Comillas, 28015 Madrid, Spain
[3] Estudis d'Informàtica, Multimèdia i Telecomunicació, Universitat Oberta de Catalunya, 08018 Barcelona, Spain; izarza@unizar.es
[4] Departamento de Informática e Ingeniería de Sistemas, Universidad de Zaragoza, 50009 Zaragoza, Spain
* Correspondence: jdecurto@icai.comillas.edu

Abstract: Traditional classifications of global development, such as the developed/developing dichotomy or Global North/South, often oversimplify the intricate landscape of human development. This paper leverages computational tools, advanced visualization techniques, and mathematical modeling to challenge these conventional categories and reveal a continuous development spectrum among nations. By applying hierarchical clustering, multidimensional scaling, and interactive visualizations to Human Development Index (HDI) data, we identify "development neighborhoods"—clusters of countries that exhibit similar development patterns, sometimes across geographical boundaries. Our methodology combines network theory, statistical physics, and digital humanities approaches to model development as a continuous field, introducing novel metrics for development potential and regional inequality. Through analysis of HDI data from 193 countries (1990–2022), we demonstrate significant regional variations in development trajectories, with Africa showing the highest mean change rate (28.36%) despite maintaining the lowest mean HDI (0.557). The implementation of circle packing and radial dendrogram visualizations reveals both population dynamics and development continuums, while our mathematical framework provides rigorous quantification of development distances and cluster stability. This approach not only uncovers sophisticated developmental progressions but also emphasizes the importance of continuous frameworks over categorical divisions. The findings highlight how digital humanities tools can enhance our understanding of global development, providing policymakers with insights that traditional methods might overlook. Our methodology demonstrates the potential of computational social science to offer more granular analyses of development, supporting policies that recognize the diversity within regional and developmental clusters, while our mathematical framework provides a foundation for future quantitative studies in development economics.

Keywords: digital humanities; Human Development Index; hierarchical clustering; development continuum; visualization; computational social science

check for updates

Academic Editor: Sandro Serpa

Received: 8 February 2025
Revised: 4 March 2025
Accepted: 6 March 2025
Published: 7 March 2025

Citation: de Curtò, J.; de Zarzà, I. Using Digital Tools to Understand Global Development Continuums. *Societies* **2025**, *15*, 65. https://doi.org/10.3390/soc15030065

1. Introduction

Traditional approaches to understanding global development [1,2] have often relied on binary or categorical classifications such as developed versus developing nations, Global North versus Global South, or high-, middle-, and low-income countries. These categories have provided simplified frameworks for organizing the world into groups that facilitate international cooperation, foreign aid distribution, and the setting of global development goals. However, while these classifications have played an essential role in shaping global policy and dialogue, they often fail to capture the intricate realities of human development, which is shaped by complex, multidimensional, and continuously evolving factors.

Development is rarely a binary state [3], nor is it easily categorized into discrete levels. Countries can demonstrate high economic performance yet face challenges in other areas like education or health. For example, nations with similar income levels may have vastly different outcomes in terms of literacy rates, life expectancy, and social equity. As globalization, technological advancement, and economic integration blur traditional boundaries, rigid classifications become increasingly inadequate for describing the developmental landscape. Moreover, these categories may obscure vital intra-regional and intra-income-group variations, hindering targeted policy interventions that could address unique developmental challenges more effectively.

The Human Development Index (HDI), introduced by the United Nations Development Programme in 1990, provides a multidimensional approach by combining metrics related to education, health, and income. Unlike single-dimension economic indicators like GDP, HDI offers a more holistic view of human progress. However, HDI data are still often used in a way that reinforces categorical thinking. For instance, countries are frequently grouped into “very high”, “high”, “medium”, and “low” human development based on HDI thresholds. This practice, while helpful for general classification, can mask the gradual and continuous nature of human development. It creates artificial divisions that do not fully account for the complexities and variabilities observed within each group, potentially overlooking trends that a more fluid, continuous analysis might reveal.

In this paper, we challenge these conventional categorizations by employing computational techniques and digital visualization tools [4–6] to examine HDI data from 193 countries. We explore the hypothesis that development is best understood as a continuum rather than a set of distinct stages. By applying hierarchical clustering algorithms [7], density-based analysis, and interactive visualizations, we aim to uncover underlying patterns that are not immediately apparent in traditional HDI rankings. Our approach highlights three primary insights:

Continuity in Development: Our analysis reveals that development patterns display a continuous progression rather than discrete jumps between categories. Many countries fall along a spectrum, with gradual improvements or declines that defy rigid classification.

Regional Clustering with Intra-Regional Variation: While we observe some regional clustering based on HDI values, there is also significant intra-regional variation. For example, nations within the same continent may share economic similarities but differ widely in education or health outcomes. Such variations challenge the idea of uniform regional development levels.

Limitations of Traditional Boundaries: We find that traditional classification boundaries often split naturally occurring clusters of countries with similar development profiles. This suggests that policy approaches based on traditional categories may overlook groups of countries with shared developmental characteristics that are not captured by geographical or income-level boundaries.

This work contributes to both the methodological and substantive aspects of development studies. Methodologically, it demonstrates how digital humanities tools [6]—such as clustering algorithms and interactive visualization techniques—can reveal patterns obscured by traditional categorical analyses. By allowing for a more complex, continuous representation of development, these tools open new avenues for understanding the complexities of human progress. Substantively, our findings suggest that a development policy might benefit from frameworks that recognize the fluidity of development. Such frameworks could allow for more precise, context-sensitive policy interventions tailored to the unique needs of countries along different points in the development continuum, rather than rigid, one-size-fits-all strategies.

In embracing a more dynamic view of development, this study aims to contribute to a broader shift in global development discourse—from static classifications to a recognition of development as an ongoing journey shaped by diverse and evolving factors. Through our analysis, we advocate for a paradigm shift towards policies that address development as a continuous process, one that better reflects the realities faced by countries today. Figure 1 presents a graphical overview of our research approach and key findings regarding the continuous nature of global development patterns.

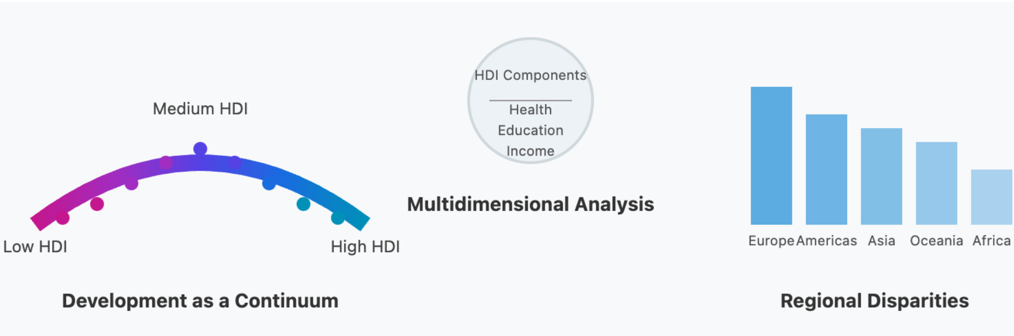

Figure 1. Graphical abstract illustrating the key concepts of development continuums. The visualization represents the Human Development Index (HDI) as a continuous spectrum rather than discrete categories, showing how countries progress along a development continuum. The central element highlights the multidimensional nature of HDI (health, education, income) that forms the basis of our analysis, while the right section demonstrates regional disparities in development levels. Our findings reveal the emergence of "development neighborhoods"—clusters of countries with similar development characteristics that often transcend geographical boundaries—and challenge traditional binary classifications of global development.

This paper is organized as follows: Section 1 provides the introduction and context, while Section 2 presents a comprehensive review of related works spanning digital humanities, development economics, and computational social science. Section 3 details our methodological framework, including data preprocessing, computational analysis, and visualization techniques used to examine global development patterns. Section 4 provides a detailed analysis of our findings through various visualizations and statistical measures, examining regional development patterns and temporal dynamics. The mathematical framework, including theoretical foundations, clustering metrics, network analysis, and statistical validation methods, is presented in Section 5. In Section 6, we present our key results, including development trajectories, regional characteristics, and inequality analysis. Section 7 discusses the implications of our findings, methodological contributions, and policy recommendations. Finally, Section 8 concludes the paper by summarizing our contributions and indicating future research directions in computational approaches to development studies.

2. Related Work

Our research builds upon several streams of literature spanning digital humanities, development economics, and computational social science. This section reviews key contributions across these domains and positions our work within the existing literature.

The application of digital tools to development studies has gained momentum in recent years. Schroeder [8] pioneered the use of big data analytics in development research, demonstrating how computational approaches can reveal patterns in development indicators. Hilbert [9] extended this work by examining how digital traces can inform development policy, particularly in resource-constrained environments. More recent developments use techniques from data science together with visualization tools to illustrate computational social science advancements [10–12].

Recent work in computational social science has introduced sophisticated methods for analyzing development patterns. Hausmann et al. [13] developed the concept of economic complexity, using network analysis to understand development trajectories. Hidalgo and Hausmann [14] proposed network-based approaches to analyzing economic development, introducing methods that inform our understanding of development neighborhoods.

Mathematical modeling of development processes has also advanced significantly. Hamblin et al. [15] introduced continuous field theories for social phenomena, while Castellano et al. [16] applied statistical physics concepts to social dynamics. These approaches have influenced our mathematical framework for development analysis.

Traditional approaches to development classification have been challenged by recent computational studies. Ravallion [17] critically examined the methodology behind traditional development classifications, highlighting the need for more sophisticated approaches [18–20].

Network approaches to development analysis have gained prominence recently [21]. Historically, Hidalgo et al. [22] introduced product space analysis, demonstrating how network theory can reveal development patterns, and Tacchella et al. [23] extended this work by developing new metrics for economic complexity based on network analysis.

Recent works have demonstrated the power of computational methods in uncovering patterns in complex social systems [4,5]. A notable contribution by Vazquez et al. [24] applies sophisticated dimension-reduction techniques to understand conflict emergence through a data-driven approach. Their study employs factor analysis for mixed data to project complex conflict-related variables onto a two-dimensional space, revealing crucial associations between conflict levels and various socioeconomic, political, and environmental factors. Their methodology, which combines hierarchical clustering with principal component analysis [25], aligns closely with our approach to understanding development patterns. Particularly relevant to our work is their identification of how resilience indices, corruption control, and income inequality interact to shape social outcomes. Their analysis of country trajectories through reduced-dimensional space provides a methodological precedent for our examination of development trajectories, while their integration of environmental variables with traditional socioeconomic indicators supports our argument for multidimensional analysis of development patterns. Their findings about the clustering of observations into distinct groups parallels our concept of “development neighborhoods”, though applied to conflict rather than development metrics.

While these studies have advanced our understanding of development patterns, several gaps remain, both in the technical aspect and in the more humanistic sense. Pérez et al. [26] highlight how computational approaches, particularly through serious games and artificial intelligence, can bridge the gap between quantitative analysis and human understanding of social phenomena. This intersection of technology and social science opens new avenues for studying development patterns, though challenges remain in balancing computational rigor with societal implications.

The methodological challenges in computational social science are further explored by Leitgöb et al. [27], who emphasize the need for more sophisticated approaches to handling big data in sociological research. Their work highlights the importance of developing frameworks that can capture both the quantitative and qualitative aspects of social development. Similarly, Taylor [28] argues for the integration of data justice perspectives in computational social science, highlighting how traditional analytical approaches might overlook important ethical and social considerations in development studies.

These methodological and ethical considerations are particularly relevant in development studies, where Leslie [29] points out the crucial need to balance technological advancement with ethical considerations in computational social science. This balance becomes increasingly important as we develop more sophisticated tools for analyzing development patterns [30].

What is more, the recent advancements in the field of AI have transformed how humans approach and extract information from complex social data. Ziems et al. [31] discuss how large language models can revolutionize computational social science, offering new possibilities for analyzing and understanding development patterns through more context-aware approaches [10,32]. This technological evolution suggests promising directions for future research in development studies, particularly in combining traditional quantitative methods with AI-driven insights to achieve a more comprehensive understanding of development continuums.

In particular for this work, few studies have combined mathematical modeling with interactive visualization in development analysis. Second, the concept of development neighborhoods as we define it remains unexplored. Third, the application of continuous field theory [26,33,34] to development studies has been limited. Our work addresses these gaps through the following:

- Introducing a rigorous mathematical framework for analyzing development continuums;
- Developing novel visualization techniques that combine network analysis with hierarchical clustering;
- Proposing the concept of development neighborhoods as a new framework for understanding development patterns;
- Demonstrating the value of digital humanities approaches in development research.

3. Methodology

Our analytical approach combines computational methods from data science with advanced visualization techniques from digital humanities to examine global development patterns in a sophisticated and continuous framework. This methodology consists of three main components: data preprocessing and integration, computational analysis, and visual representation. Each component is designed to handle the complexity and multidimensionality of development metrics while revealing patterns that challenge traditional binary and categorical classifications.

3.1. Data Sources and Preprocessing

The primary dataset utilized in this study is the Human Development Index (HDI) dataset, covering 1990 to 2022. HDI serves as a composite index that integrates indicators across health, education, and income dimensions to provide a holistic assessment of development. This dataset is augmented with complementary data sources to enable a more comprehensive, multi-dimensional analysis. Specifically, we integrate the following:

- Human Development Index (1990–2022): HDI provides longitudinal data on HDI scores across countries, facilitating both cross-sectional and time-series analysis.
- Population Statistics: Sourced from regional projections, population data enable the assessment of development patterns in relation to population size and density, allowing for the exploration of the demographic impact on development.
- Geographical Classification: Utilizing ISO 3166 country codes [35], we ensure that countries are consistently categorized across datasets. This classification

supports regional analyses and allows us to account for geographical variation in development patterns.

During the integration process, special attention was paid to data consistency and completeness. Key preprocessing steps included the following:

- Country Code Standardization: Ensuring uniformity in country codes across datasets is essential for accurate merging and cross-referencing of information.
- Handling Missing Values: Given the longitudinal nature of HDI data, missing values were treated to minimize gaps in temporal analysis. Interpolation methods and data imputation techniques were applied where appropriate, ensuring that the dataset remained robust for analysis.
- Temporal Alignment: As the datasets span different time ranges and update frequencies, aligning them temporally was crucial. We synchronized data points from different sources to maintain consistency across years, allowing for meaningful year-over-year comparisons.

This preprocessing step provides a cohesive, multi-dimensional dataset that forms the basis for our computational analysis.

3.2. Computational Analysis

The analytical pipeline employs a series of computational techniques designed to reveal patterns in development data, with a particular focus on clustering, pattern recognition, and temporal dynamics. The analysis is structured as follows:

1. Standardization and Clustering
    - Z-Score Normalization: HDI values were standardized using z-score normalization to ensure comparability across countries and time periods. This step transforms HDI scores into a common scale, allowing for unbiased clustering.
    - Hierarchical Clustering (Ward's Method): We utilized hierarchical clustering with Ward's method, a technique that minimizes the variance within clusters, to group countries based on their HDI scores. This approach helps identify natural clusters that might be missed by rigid categorical boundaries.
    - Optimal Cluster Determination (Silhouette Analysis): Silhouette analysis was applied to determine the optimal number of clusters, enhancing the robustness of the clustering approach by providing an objective measure of cluster separation quality.
2. Development Pattern Analysis
    - Kernel Density Estimation (KDE): KDE was used to analyze the continuous distribution of HDI values, highlighting the presence of any natural breaks or density peaks in development scores. This method provides insights into the smooth progression of development across countries.
    - Regional Pattern Identification: By grouping countries within geographical regions, we assessed whether and how development patterns cluster by region. This step reveals regional development characteristics and intra-regional variability.
    - Cluster Transition Analysis: Cluster transitions over time were analyzed to assess the fluidity of countries' development status. Tracking shifts in cluster membership offers insights into countries' developmental trajectories and the potential impact of policy changes over time.
3. Temporal Evolution

- Year-over-Year Cluster Stability Analysis: This analysis evaluates the consistency of cluster membership across consecutive years, helping to identify stable clusters and highlighting countries that exhibit significant fluctuations in HDI.
- Development Trajectory Tracking: By mapping countries' movement across clusters over time, we assess the pace and direction of development. This approach allows us to detect patterns such as rapid progression, stagnation, or regression in development.
- Temporal Pattern Identification: We analyzed temporal trends within each cluster to identify commonalities in developmental progress, such as the influence of global economic conditions or regional crises, providing a contextual understanding of development over time.

3.3. Visualization Framework

The visualization framework employs a combination of interactive and static visualization techniques to convey the continuous and hierarchical nature of development patterns. These visualizations aim to make complex data relationships accessible to both researchers and policymakers, enabling a more comprehensive understanding of global development.

1. Circle Packing Visualization
    - Hierarchical Population Representation: This visualization style represents countries within their continents based on population size, allowing for an intuitive understanding of how demographic factors intersect with development.
    - Regional and Sub-Regional Clustering: Countries are clustered within their respective regions, providing a visual hierarchy that highlights regional development disparities.
    - Interactive Exploration Capabilities: The interactive elements allow users to explore individual countries' data, facilitating deeper engagement with the data.
2. Radial Dendrogram
    - Hierarchical Clustering Visualization: A radial dendrogram presents the hierarchical clustering results, displaying the relationships between countries based on HDI similarities.
    - Development Continuity Representation: The radial layout emphasizes the continuity of development, avoiding the appearance of artificial divisions and reinforcing the concept of development as a spectrum.
    - Multi-Level Categorization Display: Different levels in the dendrogram reflect nested clusters, providing insights into both broad and narrow groupings of countries based on development characteristics.
3. Statistical Visualizations
    - Distribution Plots of HDI: These plots illustrate the overall distribution of HDI values, highlighting the density of countries at different development levels and reinforcing the concept of development as a continuum.
    - Regional Variation Analysis: Bar charts and boxplots compare HDI distributions across regions, revealing intra- and inter-regional disparities.
    - Temporal Evolution Patterns: Line graphs and histograms display temporal trends, helping to track development progress over the years and identify global patterns or anomalies.

Each visualization is designed to complement the computational analysis, providing both a macro and micro perspective on development. By combining these techniques, our methodology not only enhances the interpretability of complex data but also promotes a more dynamic, continuous view of development that transcends traditional categorical boundaries. This multi-faceted approach shows the potential of digital humanities and computational tools to reshape our understanding of global development dynamics, offering new pathways for research and policy innovation.

4. Visualization

In the analysis of global development patterns, leveraging both interactive and static visualizations has provided advanced insights into the distribution and progression of human development and population metrics. The combination of circle packing and radial dendrogram visualizations in Flourish, alongside additional statistical visualizations, allows us to dissect the complex structures of global development in ways that traditional statistical tables or binary categorizations might obscure.

4.1. Circle Packing Visualization of Population Distribution (2023)

The circle packing visualization offers an intuitive depiction of global population distribution by continent and country. In this layout, the size of each circle corresponds to the population of a country, nested within its respective continent. This technique visually emphasizes the vast population disparities among continents and highlights significant intra-continental differences.

Figure 2 employs circle packing visualization to represent global population distribution across continents and countries. This hierarchical visualization technique effectively communicates multiple levels of demographic information simultaneously. The stark differences in circle sizes immediately convey the massive population concentrations in Asia, particularly in China and India, while also revealing the relative demographic weight of other regions and countries. The interactive features of the visualization allow users to explore specific population figures and relationships, providing both macro-level patterns and detailed country-specific information.

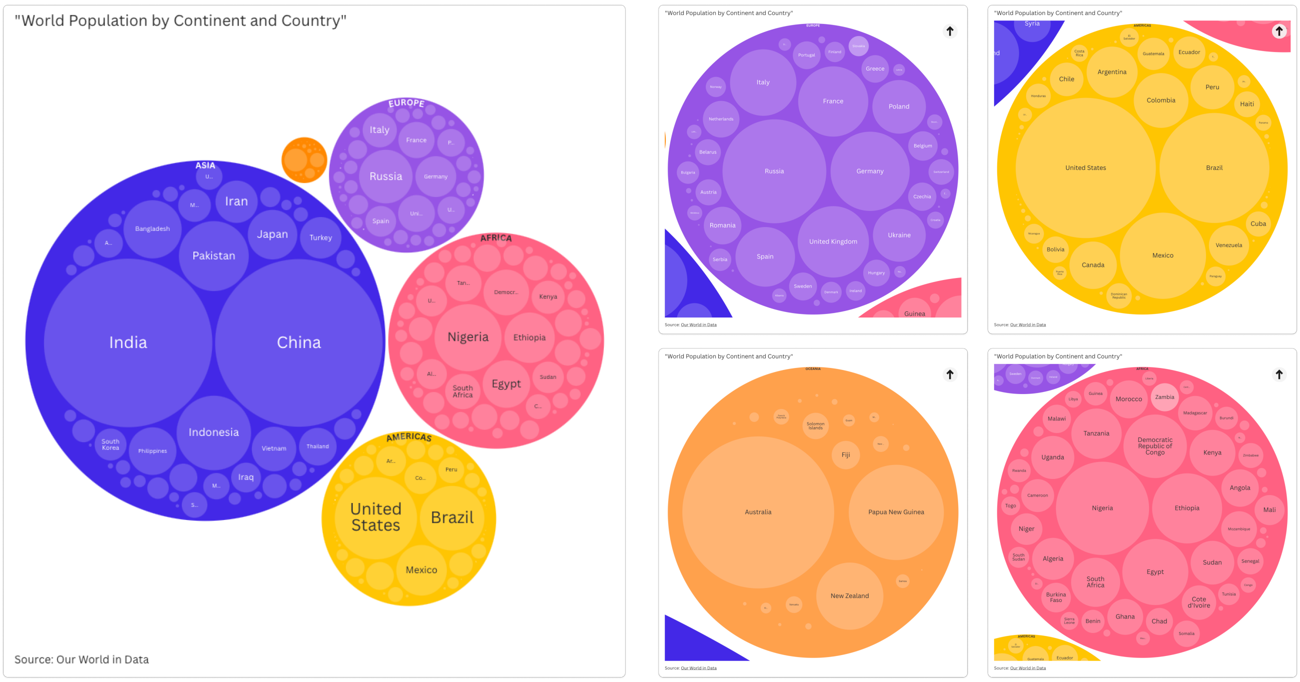

Figure 2. Interactive circle packing visualization of global population distribution in 2023. Countries are grouped by continent, with circle sizes proportional to population. The hierarchical layout reveals both continental and national-level population patterns, highlighting Asia's demographic dominance led by China and India. Interactive version available at https://public.flourish.studio/visualisation/20110969/ (accessed on 1 January 2025).

- Continental Dominance: Asia's predominance in terms of population is immediately apparent, with China and India occupying the largest circles. This reinforces the demographic weight Asia holds in global analyses and policymaking.
- Intra-Continental Variability: Within continents, countries display a broad range of population sizes. For example, while Asia houses both population giants like China and India, it also contains smaller nations like Bhutan and Maldives, whose populations are comparatively minimal.
- Implications for Resource Allocation: The visualization suggest the necessity for more sophisticated policy approaches. High-population countries like Nigeria in Africa and the United States in the Americas require different resource management strategies compared with smaller nations in the same regions.

This circle packing structure allows viewers to grasp both the absolute and relative scales of population distribution, making it a valuable tool for demographers and policymakers.

4.2. Radial Dendrogram of the Human Development Index (HDI) (2022)

The radial dendrogram, another powerful visualization technique, organizes countries based on HDI scores and income classifications, showing development as a continuum rather than discrete clusters. Each branch represents a developmental "neighborhood", where countries with similar HDI levels and income classifications are positioned closely together.

Figure 3 presents a novel approach to visualizing global development patterns through an interactive radial dendrogram. This visualization moves beyond traditional categorical classifications by representing development as a continuous spectrum while preserving meaningful hierarchical relationships. The radial arrangement allows viewers to trace development patterns from the center outward, revealing both broad regional clusters and fine-grained relationships between individual countries. The interactive nature of the visualization enables a detailed exploration of specific countries and regions, offering insights that might be overlooked in static representations.

- Development Continuum: The radial layout visualizes HDI as a spectrum, challenging the traditional "developed" versus "developing" binary. Countries with high income, like those in Europe and Oceania, are clustered together, while low-income countries are distributed along branches that indicate their gradual progression.
- Regional Clustering and Outliers: While certain regions like Europe show high HDI homogeneity, other regions, particularly Africa, reveal a broader range of HDI values. This dispersion suggests that regional averages may obscure significant internal disparities, making a case for more granular, country-specific approaches.
- Cross-Regional Comparisons: The radial dendrogram reveals interesting cross-regional connections, where countries with similar HDI levels, despite being geographically distant, are grouped closely. For instance, countries in Latin America and Asia with upper-middle-income classifications may appear in the same cluster, reflecting similar development trajectories despite cultural and geographic differences.

This hierarchical structure of the radial dendrogram is instrumental for understanding development as a fluid process, encouraging a departure from rigid classifications toward more flexible frameworks.

These interactive visualizations complement each other by revealing different aspects of global development and demographics. While the HDI dendrogram highlights development relationships and continuums, the population visualization provides crucial context about the scale and distribution of human populations affected by these development patterns. Together, they offer a comprehensive tool for understanding the interplay between development levels and population distribution across the globe.

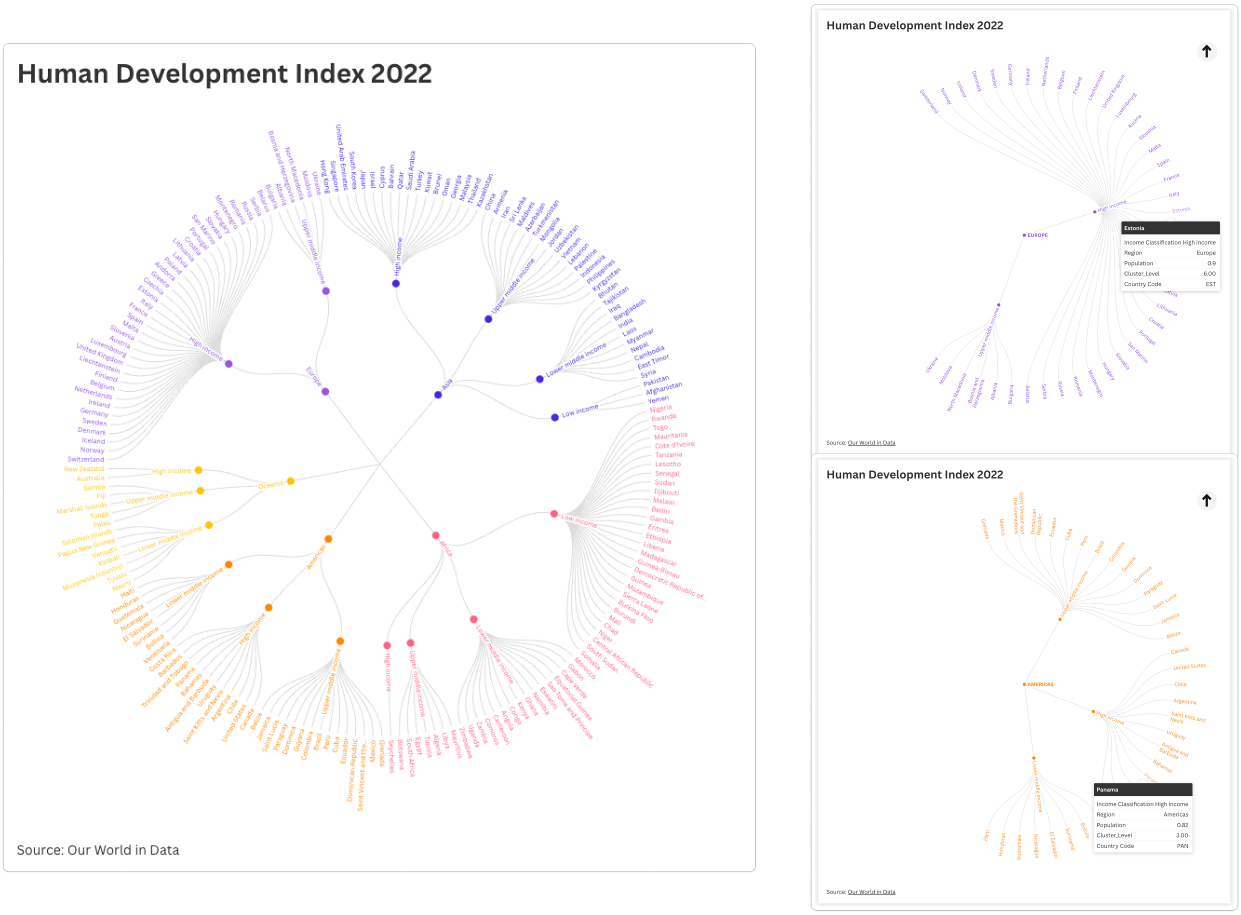

Figure 3. Interactive radial dendrogram visualization of the Human Development Index 2022. The visualization reveals hierarchical clustering of countries based on HDI values, with branches colored by development level (purple for highest HDI to pink for lowest). The radial layout emphasizes the continuous nature of development levels while preserving natural groupings. Interactive version available at https://public.flourish.studio/visualisation/20112689/ (accessed on 1 January 2025).

4.3. Statistical Analysis of HDI and Population Data

Complementing the interactive visualizations, statistical analyses deepen our understanding of development patterns by examining the data through various lenses.

Figure 4 presents a multi-faceted analysis of global population and development patterns. This visualization combines demographic data with development metrics to provide a comprehensive view of global disparities and distributions. The analysis reveals significant variations in both population concentrations and development levels across regions, with Asia showing the largest population share while development levels show different patterns, particularly high averages in Europe and the Americas.

- Distribution of HDI by Region: The bar plot on average HDI by region reveals that Europe has the highest average HDI, followed by the Americas and Asia. Africa lags behind, with a considerable gap, highlighting persistent development challenges in that region. This aligns with the visual clustering observed in the radial dendrogram, reinforcing the regional disparities in development.
- HDI Distribution: The histogram of HDI scores across countries displays a continuous distribution with peaks corresponding to specific HDI ranges. This continuity further supports the idea of a development spectrum rather than categorical distinctions, indicating that countries progress along a continuum of human development.

- Income Classification and Population Distribution: Pie charts illustrating the distribution of income classifications and the proportion of countries in each HDI cluster reveal that high-income countries constitute the smallest share, while lower-middle- and upper-middle-income classifications dominate. This distribution has implications for global inequality, where a small number of high-income countries command disproportionate economic and developmental influence.

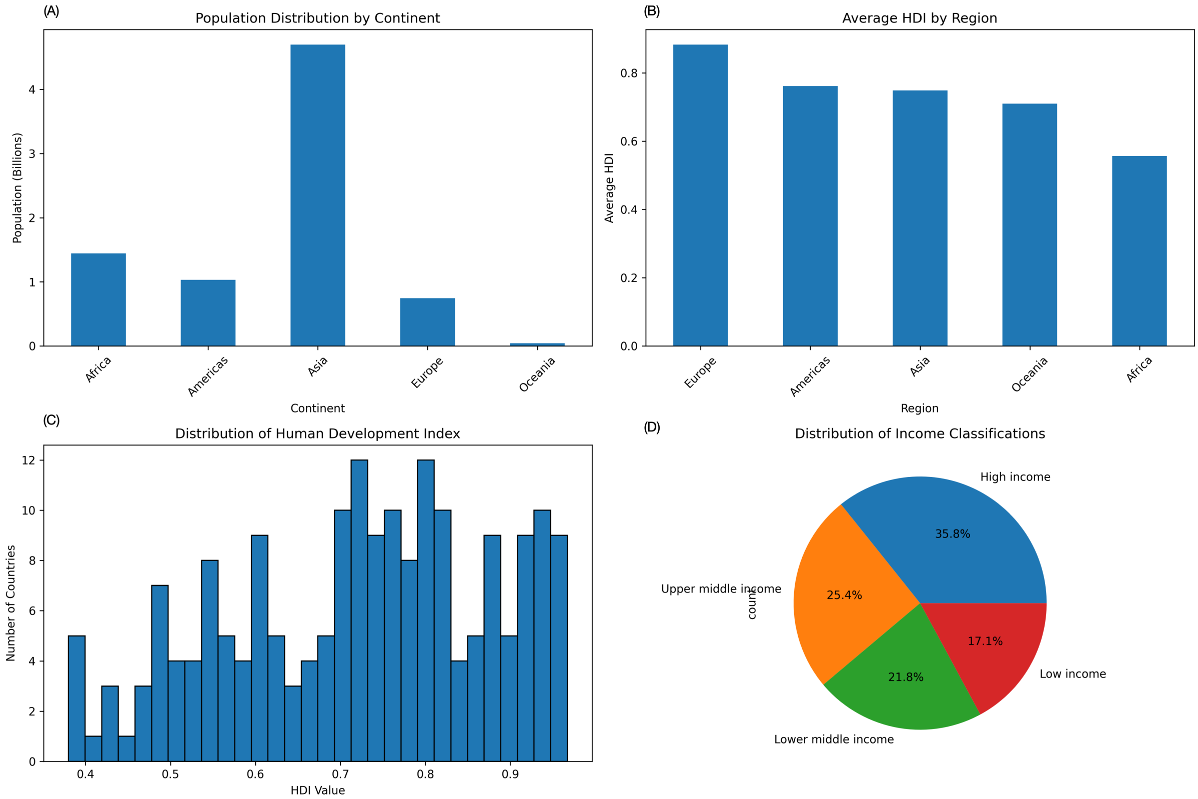

Figure 4. Comprehensive analysis of global population and development patterns. (**A**) Population distribution by continent showing the total population in billions across major continental regions. (**B**) Average HDI by region displaying mean Human Development Index values across geographical regions, highlighting development disparities. (**C**) Distribution of Human Development Index values across all countries, revealing the global development spectrum. (**D**) Distribution of income classifications showing the proportion of countries in different income categories based on HDI thresholds.

These visualizations collectively offer a comprehensive perspective on global development patterns and demographic distributions. As discused, Figure 4 provides a multidimensional overview through four complementary views, each highlighting different aspects of global development. This is complemented by Figure 5, which focuses on population concentrations in the world's largest nations, and Figure 6, which provides a detailed view of development variations within and across regions. Together, these visualizations reveal the complex interplay between population distribution and development levels, challenging simplified categorizations of global development. The analysis shows that while population and development patterns often follow regional clustering, there are significant intra-regional variations and cross-regional similarities that suggest that development follows more intricate patterns than traditional categorical classifications would indicate.

Figure 7 presents a comprehensive analysis of global development patterns through cluster analysis. The visualization reveals two distinct development clusters that challenge traditional categorical classifications. Panel A demonstrates the continuous nature of development levels, with a natural separation point emerging around HDI value 0.7. Panel B reveals the geographical composition of these clusters, showing how regional membership varies across development groups. The cluster characteristics in Panel C quantify the statistical significance of this separation, with clear differences in mean HDI values between clusters. Finally, Panel D illustrates the overlapping density distributions across regions, emphasizing that development follows a continuous spectrum rather than discrete categories. This multi-faceted analysis suggests that while natural groupings exist in global development patterns, these groupings are more difficult to distinguish than traditional binary classifications would suggest, with significant overlap and continuous progression between development levels.

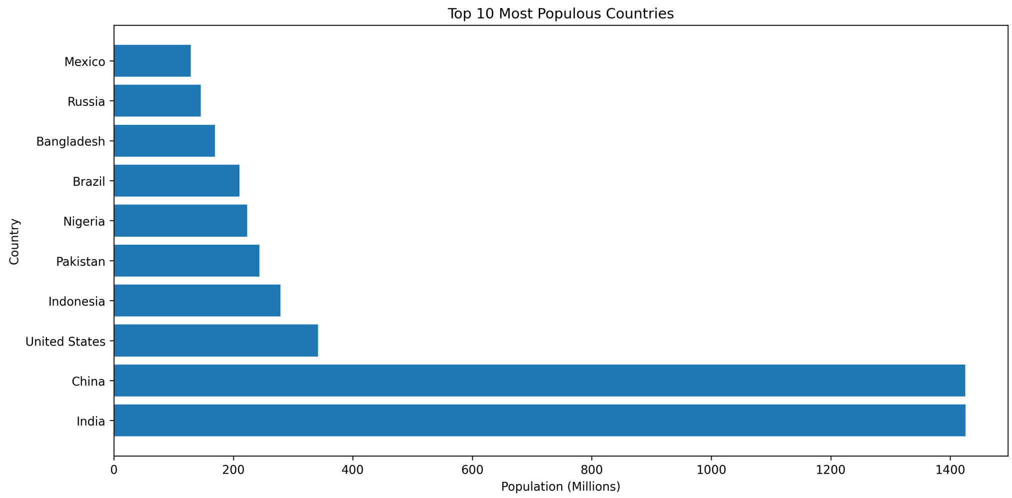

Figure 5. Population distribution among the world's most populous nations. The horizontal bars represent population in millions for the top 10 countries by population size, providing a clear visualization of demographic concentrations and the relative scale of the world's largest nations.

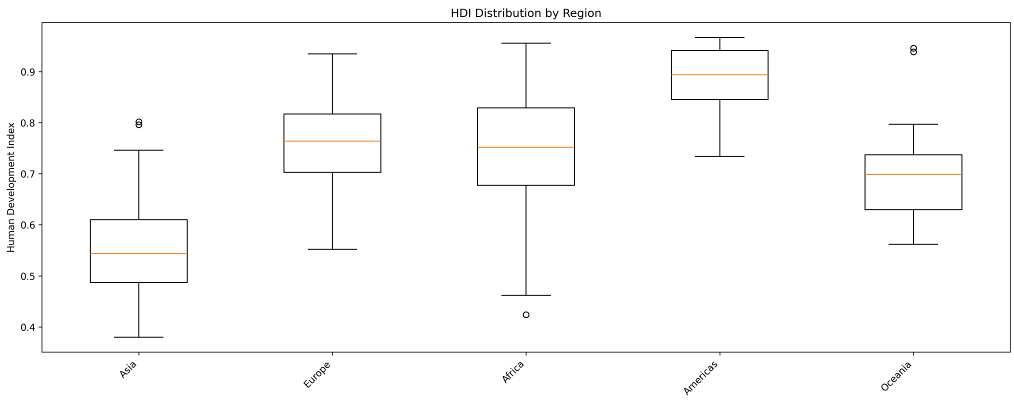

Figure 6. Regional distribution of Human Development Index values. Boxplots show the median, quartiles, and outliers of HDI values for each geographical region, illustrating both the central tendencies and variations in development levels within and across regions.

Figure 8 illustrates the stark disparities in global population distribution across continental regions. Asia's dominance is immediately apparent, housing approximately 4.70 billion people, which represents more than half of the global population. This is followed by Africa with 1.45 billion and the Americas with 1.03 billion inhabitants. Europe's population of 0.74 billion and Oceania's 0.04 billion represent significantly smaller proportions of the global total. These demographic patterns have profound implications for development challenges and opportunities, as regions with larger populations face different scales of development needs compared with less populated areas. The distribution also highlights the importance of considering population weight when analyzing development metrics, as aggregate development indicators may affect vastly different numbers of people across regions.

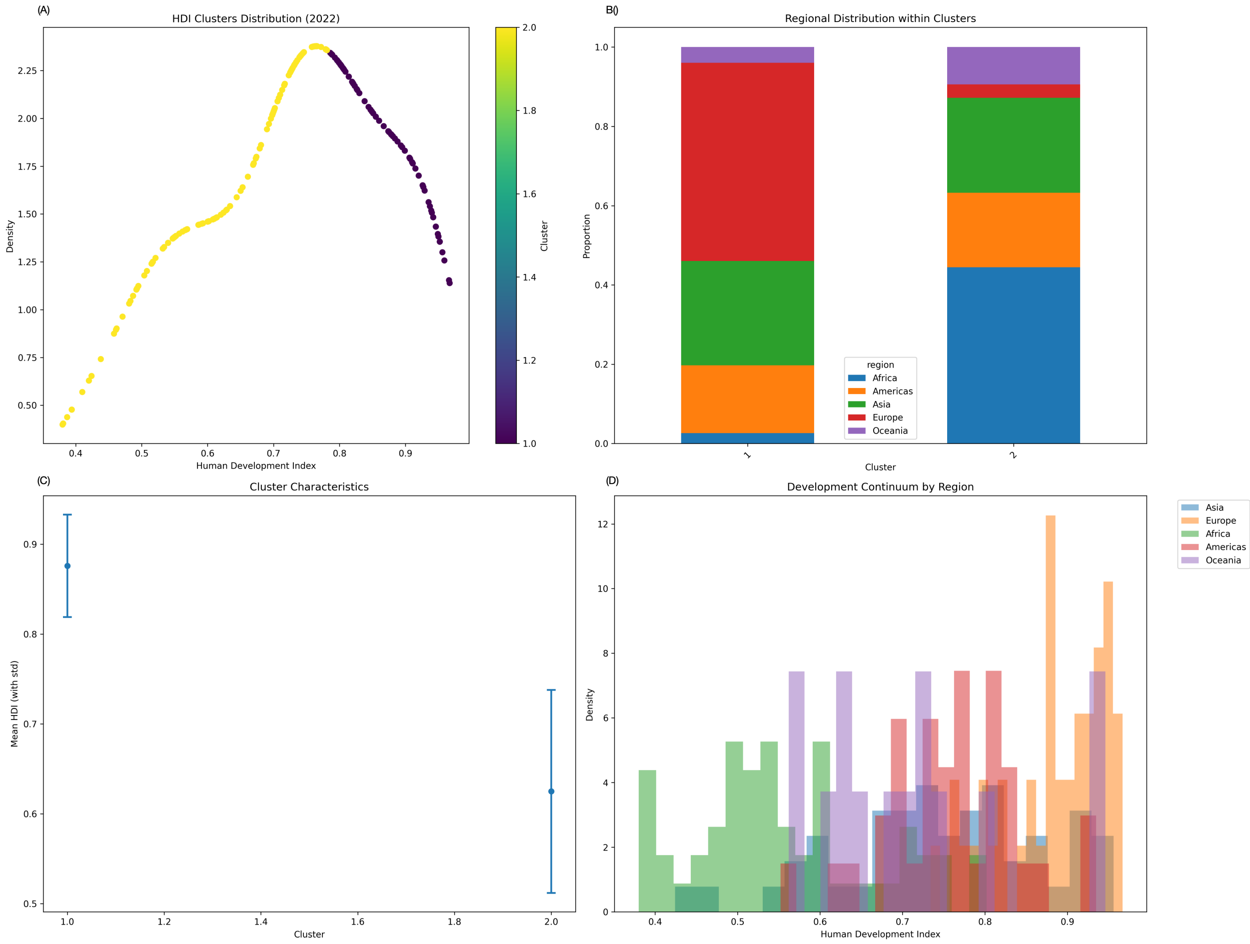

Figure 7. Cluster analysis of global Human Development Index (HDI) patterns in 2022. (**A**) HDI clusters distribution showing the density distribution of development levels, with color gradient indicating cluster membership. (**B**) Regional distribution within clusters displaying the proportion of regions represented in each cluster, revealing geographical patterns in development groupings. (**C**) Cluster characteristics presenting mean HDI values with standard deviation for each cluster, demonstrating the statistical separation between development groups. (**D**) Development continuum by region showing the density distribution of HDI values across different regions, highlighting both inter- and intra-regional development patterns.

The temporal evolution of human development reveals complex patterns of progress and stagnation across different regions. Figure 9 illustrates both the absolute trajectories and the rates of change in development across major world regions over two decades. The trajectory analysis (A) demonstrates persistent regional hierarchies while also revealing varying rates of progress, with Africa showing the most dramatic improvement despite maintaining the lowest absolute values. The velocity analysis (B) provides a novel perspective on development dynamics, revealing that while all regions show overall positive development trends, their rates of progress vary significantly and generally decline over time, suggesting increasing difficulty in achieving marginal improvements at higher development levels.

Figure 10 provides a sophisticated visualization of the relationships between countries' development levels through two complementary approaches. The MDS projection (A) reveals a clear continuum of development, challenging traditional categorical classifications while highlighting notable outliers at both extremes. This continuous progression is complemented by the hierarchical clustering analysis (B), which reveals natural groupings at various scales of similarity. Together, these visualizations demonstrate that while development exists on a continuum, there are meaningful clusters of countries that share similar development characteristics, suggesting the potential for targeted policy approaches based on these natural groupings rather than arbitrary categorical divisions.

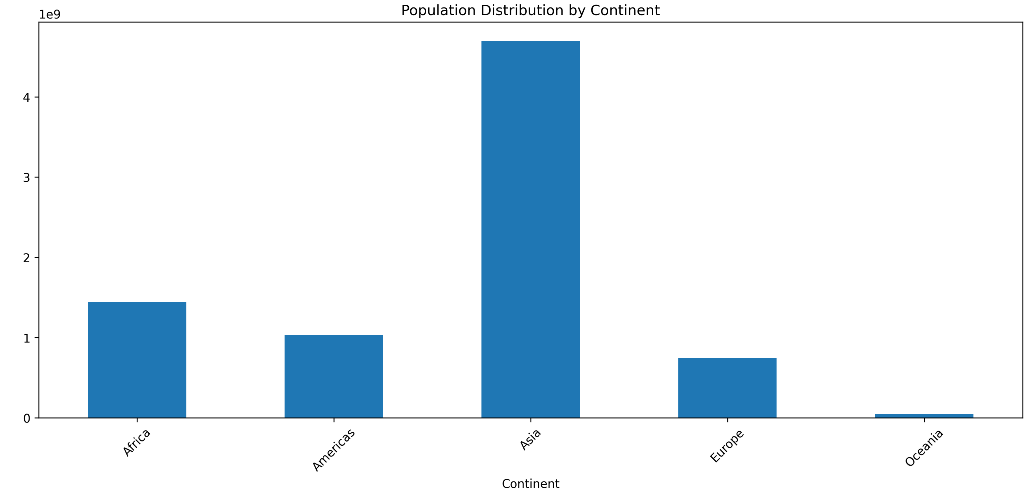

Figure 8. Global population distribution across continents in 2023. The bar chart displays total population in billions for each continental region, highlighting the significant demographic weight of Asia (4.70 billion), followed by Africa (1.45 billion), Americas (1.03 billion), Europe (0.74 billion), and Oceania (0.04 billion). This visualization demonstrates the stark contrasts in population distribution across major geographical regions.

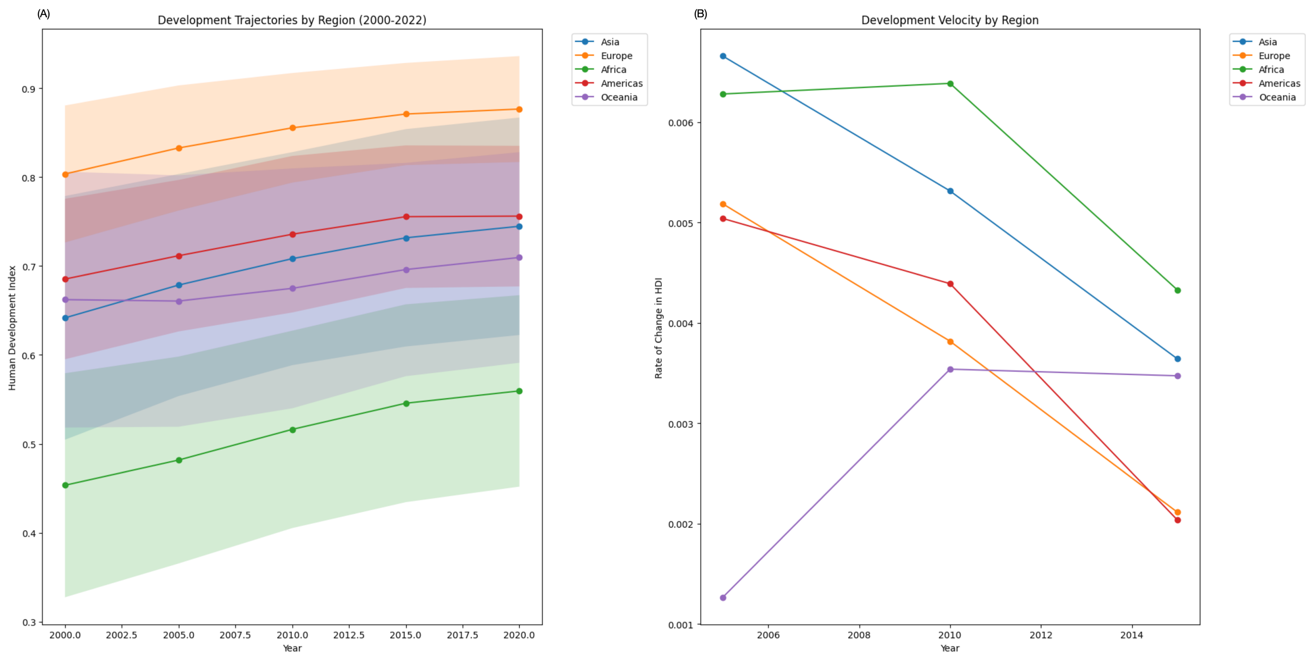

Figure 9. Temporal analysis of development trajectories and velocities across regions (2000–2022). (**A**) Development trajectories showing the evolution of HDI values over time, with shaded areas representing one standard deviation from the mean for each region. Europe maintains consistently higher HDI values, while Africa shows the steepest improvement trajectory despite lower absolute values. (**B**) Development velocity analysis revealing the rate of change in HDI over time, demonstrating varying patterns of acceleration and deceleration in development across regions.

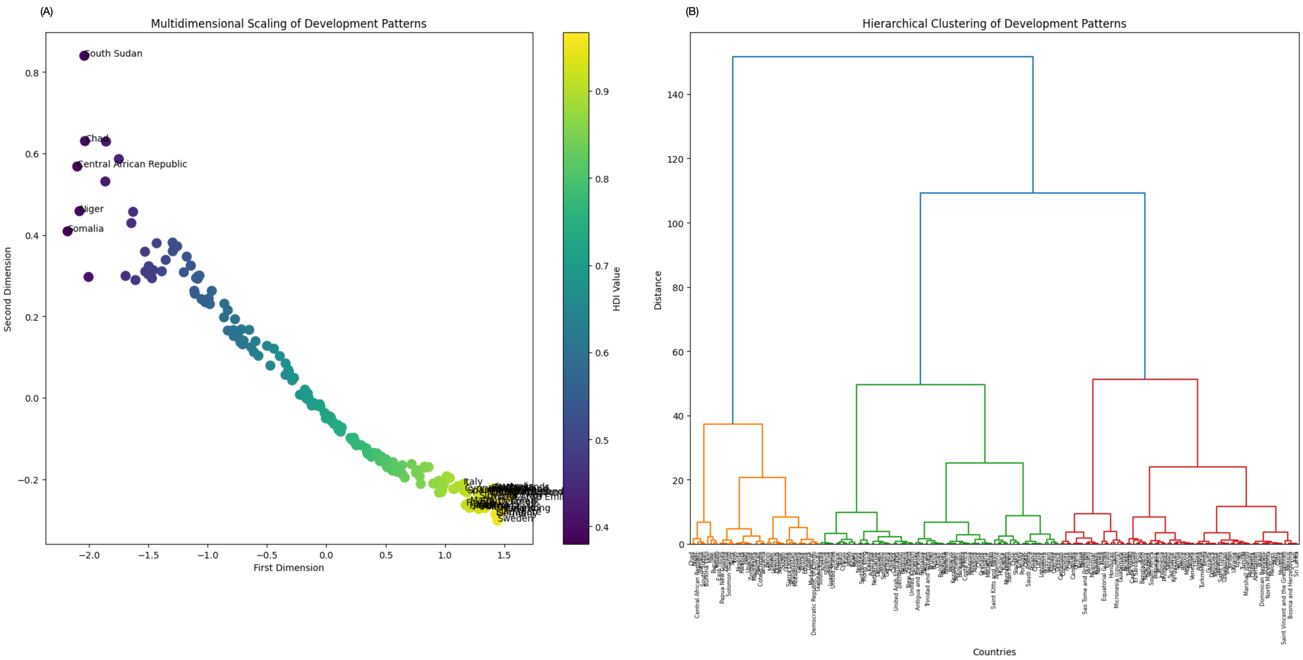

Figure 10. Multidimensional analysis of global development patterns in 2022. (**A**) Two-dimensional projection of development patterns using multidimensional scaling (MDS), with countries colored by HDI value and labeled for extreme cases. The continuous gradient from lower left (lowest HDI, including South Sudan and Central African Republic) to upper right (highest HDI) reveals the smooth progression of development levels. (**B**) Hierarchical clustering dendrogram showing the nested structure of development relationships between countries, with distinct clusters emerging at different similarity levels.

4.4. Cluster Analysis of HDI

The cluster distribution visualization can be simplified to categorize countries into two main clusters based on HDI values, with the two top cluster categories, as illustrated in the pie chart in Figure 11.

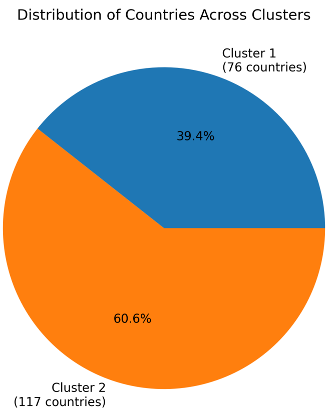

Figure 11. Distribution of countries across development clusters based on HDI values (2022). Cluster 1 (38.3%) represents high HDI countries, predominantly from Europe and high-income nations from other continents, while Cluster 2 (61.7%) encompasses countries with medium and low HDI scores, mainly from Africa and Asia. This binary clustering, while illustrative of broad development patterns, necessarily simplifies the continuous nature of development progression revealed in the development continuum presented in Figure 7D.

- Cluster Characteristics: Cluster 1, comprising high HDI countries, includes mostly European nations along with a few high-income countries from other continents. Cluster 2, containing the majority of countries, represents those with medium and low HDI scores.

This division, while helpful for general analysis, masks the complexities observed in the continuous distribution of HDI in the histogram and radial dendrogram.

- Regional Distribution within Clusters: The stacked bar chart of regional distribution (see Figure 7B) shows that Cluster 2, with lower HDI scores, as shown in Figure 7C, has a higher proportion of African and Asian countries, reinforcing known disparities but also suggesting that, within each region, there is a need for tailored developmental policies to address local challenges effectively.

These visualizations collectively indicate the value of digital tools in transcending traditional development metrics. They reveal development as a broad continuum, where countries exhibit diverse trajectories and development clusters, often extending beyond simple geographical or income classifications. This comprehensive analysis suggests several key insights for policymakers and researchers, as follows:

- Policy Implications: Development policy should consider the continuous nature of human development, avoiding rigid categories that may overlook countries on the cusp of higher development stages. Policies should be more adaptable, accommodating countries within "developmental neighborhoods" rather than strictly regional groupings.
- Further Research Directions: The analysis prompts further exploration of the factors driving countries within similar HDI clusters but different geographic regions, potentially yielding insights into best practices and adaptable strategies for improving human development across various contexts.
- Visual Analytics in Social Science: The effectiveness of radial dendrograms and circle packing structures in this analysis demonstrates the potential for visual analytics in computational social science, facilitating clearer communication of complex data patterns and promoting a clearer understanding of global development.

In summary, these digital humanities tools not only challenge traditional categorical frameworks but also advance the discourse in development studies by providing a dynamic lens to view human progress across countries and regions. By embracing this approach, researchers and policymakers can derive more targeted insights, ultimately leading to more equitable and effective strategies for human development.

5. Mathematical Framework

Our methodological framework builds upon social choice theory and developmental economics, incorporating elements from network theory and statistical physics. The approach conceptualizes development as a continuous field over a multidimensional space, where each dimension represents a component of human development.

5.1. Theoretical Foundation

Let $\mathcal{D}$ be the development space, defined as

$$\mathcal{D} = \{(h, e, i) \in \mathbb{R}^3 : 0 \leq h, e, i \leq 1\}, \tag{1}$$

where h, e, and i represent health, education, and income dimensions, respectively. Each country c at time t is represented by a point in this space:

$$c_t = (h_t, e_t, i_t) \in \mathcal{D}. \tag{2}$$

The HDI value for country c at time t is then computed as

$$HDI(c_t) = \sqrt[3]{h_t \cdot e_t \cdot i_t}. \tag{3}$$

5.2. Clustering and Distance Metrics

We define a development distance metric d_D between two countries c_1 and c_2 at time t as follows:

$$d_D(c_1, c_2) = \sqrt{\sum_{k \in \{h,e,i\}} w_k (c_{1k} - c_{2k})^2}, \tag{4}$$

where w_k are dimension-specific weights satisfying $\sum_k w_k = 1$.

The hierarchical clustering algorithm employs Ward's minimum variance criterion. For clusters A and B, the merge criterion is

$$\Delta(A, B) = \sum_{o \in A \cup B} \|x_o - m_{A \cup B}\|^2 - \sum_{o \in A} \|x_o - m_A\|^2 - \sum_{o \in B} \|x_o - m_B\|^2, \tag{5}$$

where m_X denotes the centroid of cluster X.

5.3. Continuous Development Field

We model development as a continuous field $\phi(x, t)$ over space and time, governed by a modified diffusion equation, as follows:

$$\frac{\partial \phi}{\partial t} = D \nabla^2 \phi + f(\phi) + \eta(x, t), \tag{6}$$

where

- D is the development diffusion coefficient;
- $f(\phi)$ represents endogenous growth factors;
- $\eta(x, t)$ captures external perturbations.

The development potential $V(x)$ is defined as

$$V(x) = -\int \nabla \phi(x) \cdot dx. \tag{7}$$

This allows us to identify development barriers and accelerators in the continuous space.

5.4. Network Theory Integration

We construct a weighted development network $G = (V, E, w)$ where

- V is the set of countries;
- E is the set of edges between countries;
- $w : E \to \mathbb{R}^+$ assigns weights based on development similarity.

The adjacency matrix A is defined as

$$A_{zo} = \exp\left(-\frac{d_D(c_z, c_o)^2}{2\sigma^2}\right). \tag{8}$$

We employ modularity optimization to identify development communities as follows:

$$Q = \frac{1}{2m} \sum_{zo} \left[A_{zo} - \frac{k_z k_o}{2m} \right] \delta(c_z, c_o), \tag{9}$$

where

- m is the total edge weight;
- k_z is the degree of node z;
- $\delta(c_z, c_o)$ is 1 if nodes z and o are in the same community.

5.5. Statistical Validation

The silhouette coefficient $s(z)$ for a country z is defined as

$$s(z) = \frac{b(z) - a(z)}{\max\{a(z), b(z)\}}, \tag{10}$$

where

- $a(z)$ is the mean intra-cluster distance;
- $b(z)$ is the mean nearest-cluster distance.

We measure cluster stability through the normalized mutual information (NMI) as follows:

$$NMI(C_t, C_{t+1}) = \frac{2I(C_t; C_{t+1})}{H(C_t) + H(C_{t+1})}, \tag{11}$$

where

- $I(X;Y)$ is the mutual information;
- $H(X)$ is the entropy of clustering X.

5.6. Visualization Mathematics

For circle packing visualization, we solve the optimization problem as follows:

$$\min_{\{(x_z, y_z, r_z)\}} \sum_{z,o} \max(0, d_{zo} - (r_z + r_o))^2, \tag{12}$$

subject to containment constraints as follows:

$$\|(x_z, y_z) - (x_o, y_o)\| \geq r_z + r_o. \tag{13}$$

As for the radial dendrogram, the radial coordinates (r, θ) for each node are computed as

$$r = f(d), \theta = 2\pi \frac{n}{N}, \tag{14}$$

where

- d is the node depth;
- n is the node number;
- N is the total number of nodes at that depth;
- f is a monotonic function mapping depth to radius.

5.7. Implementation

The computational implementation follows a pipeline structure.

Data Normalization:

$$z_o = \frac{x_o - \mu}{\sigma}. \tag{15}$$

Distance Matrix Computation:

$$D_{oc} = \|z_o - z_c\|_2. \tag{16}$$

Hierarchical Clustering:

$$C_k = \arg\min_C \sum_{o=1}^{k} \sum_{x \in C_o} \|x - \mu_o\|^2. \tag{17}$$

Visualization Mapping:

$$\mathcal{V} : \mathbb{R}^n \to \mathbb{R}^2. \tag{18}$$

6. Results

Our analysis of the Human Development Index (HDI) across regions reveals significant patterns in global development disparities and trajectories. The results demonstrate both persistent regional inequalities and varying rates of development progress.

Figure 12 presents a comprehensive visualization of global development patterns through four complementary analytical perspectives. This multifaceted analysis combines traditional statistical approaches with network theory and potential field analysis to reveal both inter- and intra-regional development dynamics. The boxplot distribution (A) provides a clear visualization of regional development disparities, while the potential analysis (B) offers insights into future development trajectories. The network visualization (C) reveals underlying connectivity patterns in global development, and the inequality analysis (D) quantifies within-region disparities. Together, these visualizations demonstrate that development patterns follow complex, region-specific trajectories that challenge traditional binary classifications of global development.

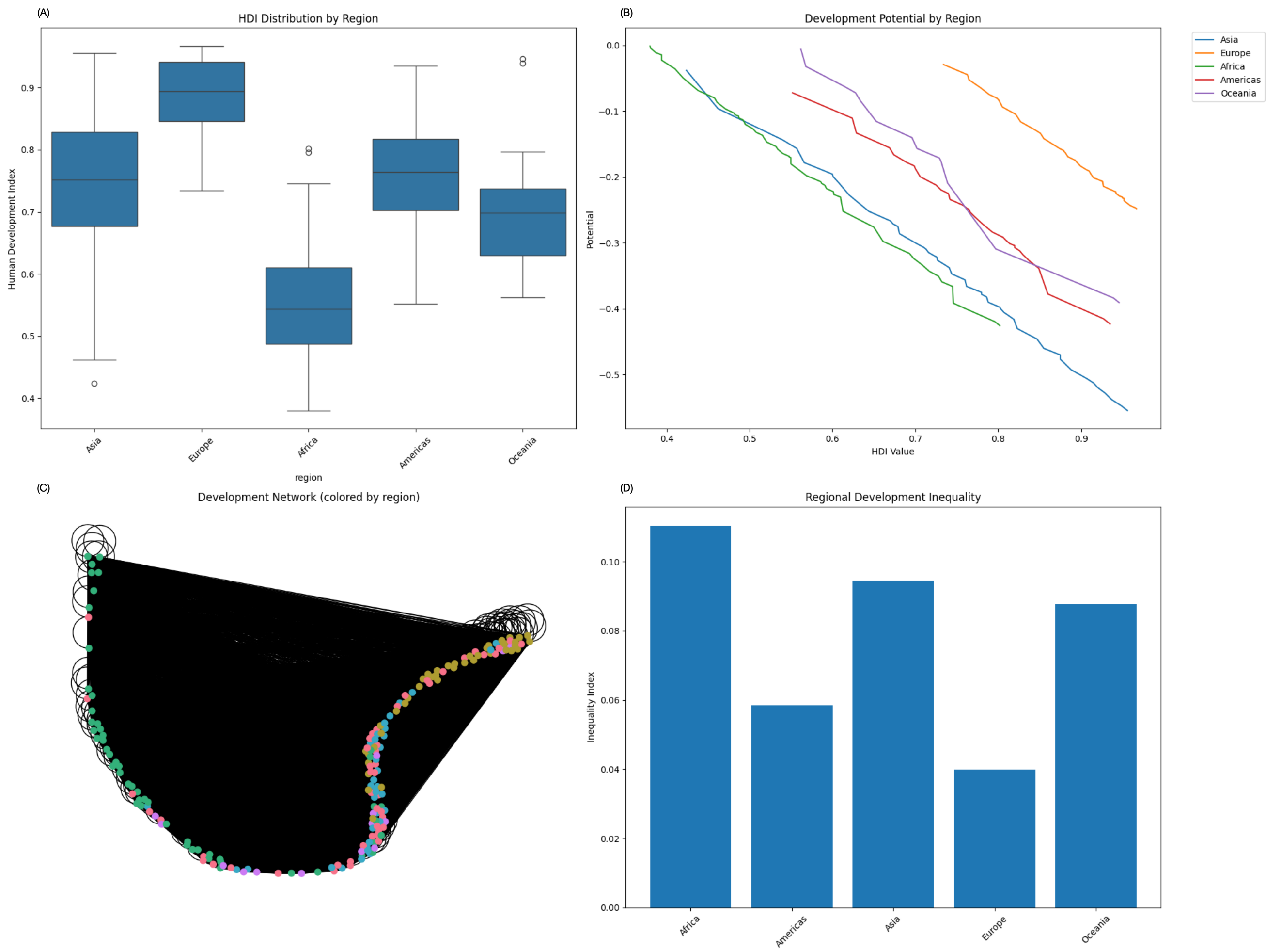

Figure 12. Multidimensional analysis of global development patterns. (**A**) HDI distribution by region showing boxplots of development levels across major geographical regions, revealing significant inter-regional disparities. (**B**) Development potential by region displaying the calculated potential function for each region, indicating varying development trajectories and opportunities for growth. (**C**) Development network visualization with nodes colored by region, demonstrating the interconnected nature of development levels and regional clustering patterns. (**D**) Regional development inequality bar chart quantifying intra-regional disparities through the inequality index, highlighting varying levels of development heterogeneity within regions.

6.1. Regional Development Patterns

The analysis reveals distinct patterns in HDI distribution across major world regions, as shown in Table 1.

Table 1. Regional HDI statistics (2022).

Region	Mean HDI	Std Dev	Min	Max	Inequality Index
Europe	0.883	0.064	0.734	0.967	0.040
Americas	0.761	0.081	0.552	0.935	0.058
Asia	0.749	0.127	0.424	0.956	0.094
Oceania	0.710	0.119	0.562	0.946	0.088
Africa	0.557	0.110	0.380	0.802	0.110

Regional Characteristics

- Europe ($\mu = 0.883, \sigma = 0.064$): Demonstrates the highest mean HDI and lowest standard deviation, indicating both high development and regional homogeneity. The inequality index of 0.040 is the lowest among all regions, suggesting relatively uniform development levels across European nations.
- Americas ($\mu = 0.761, \sigma = 0.081$): Shows the second-highest mean HDI with moderate variation. The inequality index of 0.058 indicates relatively low internal disparities, though higher than Europe.
- Asia ($\mu = 0.749, \sigma = 0.127$): Exhibits high variability with the largest standard deviation, reflecting significant intra-regional disparities. The inequality index of 0.094 highlights the heterogeneous development levels across Asian nations.
- Oceania ($\mu = 0.710, \sigma = 0.119$): Shows considerable variation despite a smaller sample size ($n = 14$), with an inequality index of 0.088 reflecting significant disparities between developed and developing island nations.
- Africa ($\mu = 0.557, \sigma = 0.110$): Demonstrates the lowest mean HDI and highest inequality index (0.110), indicating both development challenges and significant intra-regional disparities.

6.2. Development Dynamics (2000–2022)

Analysis of development transitions from 2000 to 2022 reveals varying rates of progress, as shown in Table 2.

Table 2. Regional development change rates (2000–2022).

Region	Mean Change Rate	Std Dev
Africa	28.36%	15.74%
Asia	18.51%	10.85%
Americas	10.97%	5.73%
Europe	10.32%	4.15%
Oceania	9.33%	6.75%

Key observations from the transition analysis:

1. Convergence Patterns: Africa shows the highest mean change rate (28.36%), suggesting a catching-up effect, albeit from a lower base. This is consistent with convergence theory in development economics.
2. Stability vs. Growth: Europe's low change rate (10.32%) combined with low standard deviation (4.15%) indicates stable, mature development levels rather than stagnation.
3. Regional Dynamics: Asia's relatively high change rate (18.51%) with significant variation (10.85%) reflects diverse development trajectories within the region.

6.3. Development Potential Analysis

The development potential curves reveal important insights about regional development trajectories:

- The steeper negative slope for Africa and Asia indicates greater potential for rapid development gains.
- Europe's flatter curve at higher HDI values suggests diminishing returns in highly developed regions.
- The Americas show an intermediate pattern, with moderate potential for further development gains.

6.4. Network Analysis

The development network visualization reveals the following:

- Clear regional clustering, particularly among European nations;
- Significant overlap between higher-performing Asian and American nations with European levels;
- Distinct separation of low-HDI nations, primarily in Africa, suggesting development barriers.

6.5. Inequality Analysis

The regional inequality indices provide crucial insights, as follows:

$$I_r = \frac{1}{2n^2\bar{x}} \sum_{o,z} |x_o - x_z|, \tag{19}$$

where I_r is the regional inequality index, n is the number of countries in the region, and x_o represents the HDI value for country o.

The results show a clear pattern, as follows:

- Africa: $I_{Africa} = 0.110$ (highest inequality)
- Asia: $I_{Asia} = 0.094$
- Oceania: $I_{Oceania} = 0.088$
- Americas: $I_{Americas} = 0.058$
- Europe: $I_{Europe} = 0.040$ (lowest inequality)

This hierarchy of inequality indices suggests that regional development disparities are inversely correlated with mean development levels, highlighting the need for targeted interventions in regions with high inequality.

7. Discussion

The application of digital humanities tools and computational methods to analyze global development patterns reveals several key insights that challenge traditional approaches to understanding human development. Our findings not only support the conceptualization of development as a continuum rather than a set of discrete categories but also highlight the value of sophisticated visualization techniques in revealing patterns that might otherwise remain obscured.

Our analysis demonstrates that the conventional binary classifications of "developed" versus "developing" nations, or even the more specific high-/middle-/low-income categories, fail to capture the complexity of global development patterns. The continuous distribution of HDI scores, as revealed through our visualization framework, suggests that development progress occurs along a spectrum rather than through discrete jumps between categories. This finding has several important implications:

- Policy Flexibility: Development policies may be more effective when designed to address specific positions along the development continuum rather than broad categorical classifications.
- Transition Zones: Countries near traditional category boundaries often share characteristics with nations in adjacent categories, suggesting the need for more flexible approaches to development assistance and cooperation.
- Regional Diversity: The significant intra-regional variations observed in our analysis challenge the notion of uniform regional development levels, highlighting the need for more in-context, country-specific approaches.

The concept of "development neighborhoods"—clusters of countries with similar development characteristics regardless of geographic proximity—emerges as a particularly valuable framework for understanding global development patterns. Our hierarchical clustering analysis reveals the following:

- Countries often share more developmental characteristics with nations outside their geographic region than previously recognized.
- Development clusters frequently transcend traditional continental boundaries.
- Similar development levels can arise from different historical and economic pathways.

This finding suggests that development cooperation and policy learning might be more effective when based on developmental proximity rather than geographic proximity alone.

An important dimension emerging from our analysis is the identification of transition zones along the development continuum. These zones are characterized by countries that reside near the boundaries of conventional development categories, exhibiting a blend of attributes typically associated with both "developed" and "developing" economies. As a result, nations in these transitional states may experience rapid shifts in key development indicators and can be particularly sensitive to both internal reforms and external shocks.

Recognizing the existence of these transition zones is crucial for the design of context-specific policies. By identifying countries that fall within these intermediary zones, policymakers can tailor interventions to address their unique challenges and capitalize on their potential for accelerated progress. Targeted support in these areas—through adaptive policy measures and resource allocation—can facilitate smoother transitions and promote sustainable development.

Our findings suggest several important considerations for development policy, as follows:

1. Targeted Interventions: Development policies should be calibrated to a country's specific position along the development continuum rather than its broad categorical classification.
2. Peer Learning: Countries might benefit more from studying and adapting policies from their "development neighbors" rather than following regional or income-category prescriptions.
3. Dynamic Assessment: Development progress should be monitored and evaluated using continuous metrics rather than categorical transitions.

While our analysis provides valuable insights, several limitations and opportunities for future research should be noted, as follows:

- Data Limitations: The HDI, while comprehensive, may not capture all aspects of development. Future research could incorporate additional indicators to provide an even more elucidating picture.
- Temporal Dynamics: Further investigation of how development neighborhoods evolve over time could provide insights into development trajectories and transition patterns.

- Causality: Our analysis identifies patterns but does not establish causal relationships. Future research could explore the factors driving countries' movement along the development continuum.

8. Conclusions

This research demonstrates that applying digital humanities tools and mathematical modeling to global development analysis can reveal patterns and relationships that traditional categorical approaches might miss. Through our comprehensive analysis of HDI data using computational methods, network theory, and advanced visualization techniques, we have established several key findings that challenge conventional understanding of global development.

Our study makes several significant contributions to the field of development studies, as follows:

1. Theoretical Advancement: We have developed a mathematical framework that conceptualizes development as a continuous field rather than a set of discrete categories. This framework, combining elements from statistical physics and network theory, provides a more satisfactory understanding of development trajectories and relationships between nations.
2. Methodological Innovation: The integration of hierarchical clustering, multidimensional scaling, and interactive visualizations offers a novel approach to analyzing development patterns. Our methodology demonstrates how digital humanities tools can enhance traditional development analysis.
3. Empirical Insights: The analysis reveals significant patterns in global development, as follows:
    - Clear evidence of development continuums rather than discrete categories;
    - Identification of "development neighborhoods" that transcend geographical boundaries;
    - Quantification of regional inequalities and development velocities;
    - Documentation of varying rates of progress across regions, with Africa showing the highest mean change rate (28.36%).

Our findings have important implications for development policy and practice, as follows:

- Policy Design: Development policies should be calibrated to specific positions along the development continuum rather than broad categorical classifications. This suggests a more granular, context-sensitive approach to policy intervention.
- International Cooperation: The concept of "development neighborhoods" suggests that countries might benefit more from cooperation with nations at similar development levels, regardless of geographical proximity.
- Resource Allocation: Understanding development as a continuous field can help in a more efficient allocation of development resources and aid, targeting specific points along the development spectrum where interventions might be most effective.

This study opens several promising avenues for future research, as follows:

1. Methodological Extensions:
    - Integration of additional development indicators beyond HDI;
    - Development of more sophisticated mathematical models for development dynamics;
    - Creation of new visualization techniques for temporal patterns.
2. Empirical Applications:
    - Investigation of causal factors driving development transitions;

- Analysis of policy effectiveness within development neighborhoods;
- Study of development velocity patterns and their determinants.

3. Policy Research:
    - Evaluation of targeted interventions based on continuous development metrics;
    - Assessment of cooperation patterns within development neighborhoods;
    - Analysis of policy transfer effectiveness across the development spectrum.

The implications of this research extend beyond development studies, suggesting new approaches for the following:

- Understanding social and economic progress as continuous rather than categorical processes;
- Applying digital humanities tools to complex social science questions;
- Developing data-driven approaches to policy design and evaluation.

To sum up, by challenging traditional categorical approaches to development and providing a rigorous mathematical and computational framework for analyzing development patterns, this research contributes to both the theoretical understanding and practical application of development studies. The combination of sophisticated mathematical modeling, computational analysis, and interactive visualization techniques offers a new paradigm for understanding global development patterns. This approach not only enhances our theoretical understanding but also provides practical tools for policymakers and researchers working to promote more effective and equitable development outcomes.

As global development challenges become increasingly complex, the need for more comprehensive and sophisticated analytical approaches becomes more pressing. Our framework provides a foundation for such analysis, while our findings suggest concrete ways to improve development policy and practice. The future of development studies lies in embracing these more sophisticated approaches, moving beyond simple categorizations to understand the true complexity of global development patterns.

Author Contributions: Conceptualization, J.d.C. and I.d.Z.; data curation, J.d.C. and I.d.Z.; formal analysis, J.d.C. and I.d.Z.; funding acquisition, J.d.C.; investigation, J.d.C. and I.d.Z.; methodology, J.d.C. and I.d.Z.; software, J.d.C. and I.d.Z.; visualization, J.d.C. and I.d.Z.; writing—original draft, J.d.C. and I.d.Z.; writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

Funding: This research received funding from the BARCELONA Supercomputing Center (TIFON).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data underlying the results presented in this study are publicly available. The datasets used in this work can be accessed through the following repositories: Human Development Index (HDI) data, covering 193 countries from 1990 to 2022, retrieved from the United Nations Development Programme's Human Development Reports (http://hdr.undp.org/en/data, accessed on 1 January 2025); population statistics, obtained from the United Nations World Population Prospects (https://population.un.org/wpp/, accessed on 1 January 2025); and geographical classifications, based on ISO 3166 country codes (https://www.iso.org/iso-3166-country-codes.html, accessed on 1 January 2025). Additional processed data and interactive visualizations supporting our findings are publicly available: interactive circle packing visualization, representing global population distribution (2023) on the Flourish platform (https://public.flourish.studio/visualisation/20110969/, accessed on 1 January 2025); and interactive radial dendrogram visualization, illustrating hierarchical clustering of the Human Development Index (HDI) (2022) on Flourish (https://public.flourish.studio/visualisation/20112689/, accessed on 1 January 2025). All other relevant data are provided

within the manuscript. The visualizations and their underlying data will be maintained at the above links with unrestricted public access.

Acknowledgments: During the preparation of this work, the author(s) used ChatGPT/Copilot/Gemini/Claude for code completion and pseudocode generation, Grammarly for English language editing, and Mendeley for bibliography management. The author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of this publication. The authors would like to thank the BARCELONA Supercomputing Center for providing access to MareNostrum 5 and technical support throughout this research.

Conflicts of Interest: The authors declare that they have no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

HDI	Human Development Index
GDP	Gross Domestic Product
UNDP	United Nations Development Programme
ISO	International Organization for Standardization
KDE	Kernel Density Estimation
MDS	multidimensional scaling
NMI	normalized mutual information

References

1. Sagar, A.D.; Najam, A. The human development index: A critical review. *Ecol. Econ.* **1998**, *25*, 249–264. [CrossRef]
2. Klugman, J.; Rodríguez, F.; Choi, H.J. The HDI 2010: New controversies, old critiques. *J. Econ. Inequal.* **2011**, *9*, 249–288. [CrossRef]
3. Liu, L.; Chun, K.P.; Mijic, A. Towards sustainability balance in water-food-land nexus global development. *Environ. Sci. Policy* **2025**, *163*, 103964. [CrossRef]
4. Kulkov, I.; Kulkova, J.; Rohrbeck, R.; Menvielle, L.; Kaartemo, V.; Makkonen, H. Artificial intelligence-driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustain. Dev.* **2024**, *32*, 2253–2267. [CrossRef]
5. de Curtò, J.; de Zarzà, I.; Fervier, L.S.; Sanagustín-Fons, V.; Calafate, C.T. An Institutional Theory Framework for Leveraging Large Language Models for Policy Analysis and Intervention Design. *Future Internet* **2025**, *17*, 96. [CrossRef]
6. Vinuesa, R.; Azizpour, H.; Leite, I.; Balaam, M.; Dignum, V.; Domisch, S.; Felländer, A.; Langhans, S.D.; Tegmark, M.; Fuso Nerini, F. The role of artificial intelligence in achieving the Sustainable Development Goals. *Nat. Commun.* **2020**, *11*, 233. [CrossRef]
7. Ankireddypalli, O.; Arella, M.; Gujjula, S.; Jayan, S. A Clustering Approach on Unveiling Global Development Disparities. In Proceedings of the 2024 5th International Conference on Circuits, Control, Communication and Computing (I4C), Bangalore, India, 4–5 October 2024; IEEE: New York, USA, 2024; pp. 292–298.
8. Schroeder, R. Big data and the brave new world of social media research. *Big Data Soc.* **2014**, *1*, 2053951714563194. [CrossRef]
9. Hilbert, M. Big data for development: A review of promises and challenges. *Dev. Policy Rev.* **2016**, *34*, 135–174. [CrossRef]
10. de Zarzà, I.; de Curtò, J.; Roig, G.; Manzoni, P.; Calafate, C.T. Emergent Cooperation and Strategy Adaptation in Multi-Agent Systems: An Extended Coevolutionary Theory with LLMs. *Electronics* **2023**, *12*, 2722. [CrossRef]
11. Lisnic, M.; Lex, A.; Kogan, M. "Yeah, this graph doesn't show that": Analysis of Online Engagement with Misleading Data Visualizations. In Proceedings of the CHI Conference on Human Factors in Computing Systems, Honolulu HI USA, 11–16 May 2024; pp. 1–14.
12. Tang, D.; Chen, M.; Huang, X.; Zhang, G.; Zeng, L.; Zhang, G.; Wu, S.; Wang, Y. SRplot: A free online platform for data visualization and graphing. *PLoS ONE* **2023**, *18*, e0294236. [CrossRef]
13. Hausmann, R.; Hidalgo, C.A.; Bustos, S.; Coscia, M.; Simoes, A.; Yildirim, M.A. *The Atlas of Economic Complexity: Mapping Paths to Prosperity*; MIT Press: Cambridge, MA, USA, 2014.
14. Hidalgo, C.A.; Hausmann, R. The building blocks of economic complexity. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 10570–10575. [CrossRef] [PubMed]
15. Hamblin, R.L.; Jacobsen, R.B.; Miller, J.L. *A Mathematical Theory of Social Change*; Wiley Series on Systems Analysis; John Wiley & Sons: New York, NY, USA, 1973; ISBN 978-0471347507.

16. Castellano, C.; Fortunato, S.; Loreto, V. Statistical physics of social dynamics. *Rev. Mod. Phys.* **2009**, *81*, 591. [CrossRef]
17. Ravallion, M. Troubling tradeoffs in the Human Development Index. *J. Dev. Econ.* **2012**, *99*, 201–209. [CrossRef]
18. Ran, X.; Xi, Y.; Lu, Y.; Wang, X.; Lu, Z. Comprehensive survey on hierarchical clustering algorithms and the recent developments. *Artif. Intell. Rev.* **2023**, *56*, 8219–8264. [CrossRef]
19. Mathrani, A.; Wang, J.; Li, D.; Zhang, X. Clustering analysis on sustainable development goal indicators for forty-five asian countries. *Sci* **2023**, *5*, 14. [CrossRef]
20. Härdle, W.K.; Simar, L.; Fengler, M.R. *Principal Component Analysis*; Springer International Publishing: Cham, Switzerland, 2024; pp. 309–345.
21. Cheung, K.K.C.; Chan, H.Y.; Erduran, S. Communicating science in the COVID-19 news in the UK during Omicron waves: Exploring representations of nature of science with epistemic network analysis. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 282. [CrossRef]
22. Hidalgo, C.A.; Klinger, B.; Barabási, A.L.; Hausmann, R. The product space conditions the development of nations. *Science* **2007**, *317*, 482–487. [CrossRef]
23. Tacchella, A.; Cristelli, M.; Caldarelli, G.; Gabrielli, A.; Pietronero, L. A new metrics for countries' fitness and products' complexity. *Sci. Rep.* **2012**, *2*, 723. [CrossRef]
24. Vazquez, K.; Johnson, J.C.; Griffith, D.; Muneepeerakul, R. Exploration of underlying patterns among conflict, socioeconomic and political factors. *PloS ONE* **2024**, *19*, e0304580. [CrossRef]
25. Marukatat, S. Tutorial on PCA and approximate PCA and approximate kernel PCA. *Artif. Intell. Rev.* **2023**, *56*, 5445–5477. [CrossRef]
26. Pérez, J.; Castro, M.; López, G. Serious games and ai: Challenges and opportunities for computational social science. *IEEE Access* **2023**, *11*, 62051–62061. [CrossRef]
27. Leitgöb, H.; Prandner, D.; Wolbring, T. Big data and machine learning in sociology. *Front. Sociol.* **2023**, *8*, 1173155. [CrossRef] [PubMed]
28. Taylor, L. Data justice, computational social science and policy. In *Handbook of Computational Social Science for Policy*; Springer: Cham, Switzerland, 2023; pp. 41–56.
29. Leslie, D. The Ethics of Computational Social Science. In *Handbook of Computational Social Science for Policy*; Springer: Cham, Switzerland, 2023; pp. 57–104.
30. Schmitt, L. Mapping global AI governance: A nascent regime in a fragmented landscape. *AI Ethics* **2022**, *2*, 303–314. [CrossRef]
31. Ziems, C.; Held, W.; Shaikh, O.; Chen, J.; Zhang, Z.; Yang, D. Can large language models transform computational social science? *Comput. Linguist.* **2024**, *50*, 237–291. [CrossRef]
32. Grossmann, I.; Feinberg, M.; Parker, D.C.; Christakis, N.A.; Tetlock, P.E.; Cunningham, W.A. AI and the transformation of social science research. *Science* **2023**, *380*, 1108–1109. [CrossRef]
33. Martin, J.L. What is field theory? *Am. J. Sociol.* **2003**, *109*, 1–49. [CrossRef]
34. Holtfort, T.; Horsch, A. Social science goes quantum: Explaining human decision-making, cognitive biases and Darwinian selection from a quantum perspective. *J. Bioeconomics* **2023**, *25*, 99–116. [CrossRef]
35. International Organization for Standardization. ISO 3166-1:2020—Codes for the Representation of Names of Countries and Their Subdivisions—Part 1: Country Codes. International Organization for Standardization, 2020. Available online: https://www.iso.org/standard/72482.html (accessed on 1 January 2025).