

Big Data-Driven Transformation of Social Science Research

Tianhuan PENG

Hunan Institute of Scientific and Technical Information, Hunan, China

*tianhuan@gmail.com

Abstract. This study examines the transformative potential of big data integration in social science research and proposes systematic approaches for implementing data-driven methodologies through institutional innovation. The methodology encompasses systematic analysis of traditional research limitations, mechanistic investigation of big data integration effects on seven critical research phases (topic identification, literature synthesis, theoretical framework development, data acquisition, analytical processing and visualization, knowledge dissemination, and outcome evaluation), and institutional design analysis for philosophy and social science laboratory development. The analysis reveals that big data fundamentally transforms social science research through multiple mechanisms. The proposed laboratory framework addresses critical implementation challenges through seven strategic dimensions: institutional awareness enhancement, differentiated development pathways, computational infrastructure strengthening, specialized tool and platform development, interdisciplinary talent cultivation, comprehensive data resource construction, and supportive policy framework establishment.

Keywords: big data, social science research, computational social science, data-driven research

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1. Introduction

The contemporary digital era has ushered in unprecedented volumes of human behavioral data, fundamentally challenging traditional paradigms in social science research. Every moment generates vast quantities of digitized traces of human activity across multiple domains—social media interactions, economic transactions, mobility patterns, and communication networks—creating a complex tapestry of information that exceeds the analytical capacity of conventional research methodologies [1]. The exponential growth of data generation, estimated at 2.5 quintillion bytes daily, presents both unprecedented opportunities and significant methodological challenges for understanding human society and social phenomena [2].

Traditional social science research methodologies, developed during eras of data scarcity, face fundamental limitations when confronting the scale, velocity, and complexity of contemporary social systems [3]. Conventional approaches—primarily relying on small-sample surveys, limited observational studies, and expert interpretation—prove inadequate for analyzing the multidimensional, interconnected, and rapidly evolving nature of digital society [4]. The emergence of cyber-physical-social systems, characterized by the integration of human behavior, technological infrastructure, and physical environments, demands methodological innovations that transcend traditional disciplinary boundaries [5].

Big data technologies offer transformative potential for addressing these methodological limitations through enhanced computational capabilities, multi-source data integration, and advanced analytical techniques [6]. The integration of machine learning algorithms, natural language processing, network analysis, and visualization technologies enables researchers to process heterogeneous datasets at unprecedented scales while uncovering patterns and relationships previously inaccessible through traditional methods [7]. This technological convergence has catalyzed the emergence of computational social science as a distinct research paradigm, combining social science theory with computational methodology and big data analytics [8].

However, the effective integration of big data approaches in social science research extends beyond technological adoption to encompass fundamental questions of research design, institutional capacity, and methodological rigor [9]. Existing literature has predominantly focused on isolated applications or theoretical

discussions without providing comprehensive frameworks for systematic integration across the entire research lifecycle [10]. Critical gaps persist in understanding how big data methodologies can be systematically embedded within traditional social science research processes while maintaining scholarly rigor and addressing ethical considerations [11].

The institutional dimensions of big data integration remain particularly underexplored. While individual researchers and small teams have demonstrated successful applications of big data techniques, scaling these approaches requires institutional innovations that can support interdisciplinary collaboration, provide adequate computational infrastructure, and develop specialized human capital [12]. The concept of philosophy and social science laboratories represents a promising institutional model for addressing these integration challenges, yet systematic analysis of their design principles and implementation strategies remains limited [13].

This research addresses these gaps by examining the comprehensive mechanisms through which big data transforms social science research and proposing systematic approaches for institutional implementation. The study makes three primary contributions: (1) systematic analysis of big data's impact across seven critical phases of the social science research lifecycle—topic identification, literature synthesis, theoretical framework development, data acquisition, analytical processing, knowledge dissemination, and outcome evaluation; (2) identification of specific limitations in traditional methodologies that big data approaches can address, including complex system analysis, data processing capacity, and temporal responsiveness; and (3) development of a comprehensive framework for philosophy and social science laboratory construction that integrates technological, human capital, and institutional dimensions.

The research methodology employs theoretical analysis combined with practical case examination to understand both the transformative potential and implementation challenges of big data integration. Drawing from computational social science, digital humanities, science policy, and institutional innovation literature, the study provides a holistic examination of the technological, methodological, and organizational dimensions of research transformation.

The findings reveal that big data integration represents a paradigmatic shift rather than incremental technological enhancement, requiring coordinated development across multiple domains including computational infrastructure, analytical capabilities, human capital development, and institutional frameworks. The proposed philosophy and social science laboratory model address these requirements through seven strategic implementation dimensions: institutional awareness, differentiated development, computational support, platform development, talent cultivation, data resource construction, and policy framework establishment.

2. Methods

This study employs a multi-dimensional analytical framework to examine the transformative mechanisms of big data integration in social science research and develop systematic implementation strategies through institutional innovation. The methodology combines theoretical analysis, process modeling, and institutional design principles to provide comprehensive understanding of both technological capabilities and organizational requirements for effective integration.

Figure 1 show the research methodology is structured around three interconnected analytical dimensions: (1) limitation assessment of traditional methodologies, (2) mechanism analysis of big data integration across research phases, and (3) institutional framework development for systematic implementation. This multi-level approach enables comprehensive examination of technological, methodological, and organizational factors influencing research transformation. The analytical framework employs process decomposition methodology, breaking down social science research into seven discrete phases to enable detailed examination of big data integration mechanisms [14]. This granular analysis approach facilitates identification of specific transformation points where technological intervention can address methodological limitations while maintaining scholarly rigor and theoretical validity.

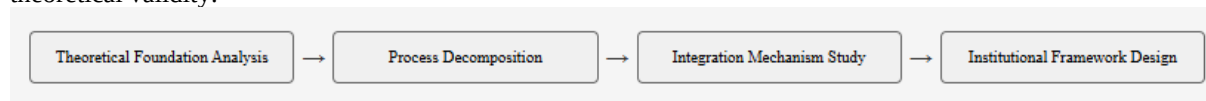


Figure 1. Integrated Analytical Methodology

2.1 Big Data Integration Mechanism Analysis

The mechanism analysis employs process tracing methodology to examine transformation effects across seven discrete research phases [15]. Each phase analysis follows a standardized evaluation protocol encompassing four analytical components: limitation identification, technological intervention characterization, capability enhancement measurement, and quality assurance consideration. For each research phase, the analysis examines: (1) specific limitations of traditional approaches, (2) big data technological interventions and their mechanisms, (3) quantifiable improvements in research capabilities, and (4) methodological considerations for maintaining

scholarly rigor. This systematic approach enables comprehensive understanding of integration benefits while identifying potential challenges and mitigation strategies [16].

The philosophy and social science laboratory framework development employs institutional design methodology drawing from organizational theory, innovation systems research, and research infrastructure studies [17]. The development process integrates technological capability requirements with organizational design principles to create sustainable institutional models for big data integration.

2.2 Data Collection and Analysis Procedures

The research employs multi-source data collection combining literature synthesis, case study analysis, and expert consultation to ensure comprehensive understanding of big data integration challenges and opportunities [18]. Data sources include academic publications, institutional reports, policy documents, and technology assessment studies spanning 2015-2024. Systematic literature review employs structured search strategies across multiple databases including Web of Science, Scopus, and specialized social science repositories. Search terms encompass "big data," "social science research," "computational social science," "digital humanities," and related terminology. Literature analysis follows PRISMA guidelines for systematic reviews with quality assessment criteria for included studies [19].

Case studies are selected using purposive sampling to represent diverse institutional contexts, technological implementations, and disciplinary applications. Analysis employs within-case and cross-case comparison methodology to identify patterns, success factors, and implementation challenges [20]. Figure 2 illustrates the comprehensive laboratory development framework with strategic implementation dimensions.



Figure 2. Strategic Implementation Components

The research methodology incorporates multiple validation mechanisms to ensure analytical rigor and methodological transparency. Validation procedures address both technical accuracy and scholarly validity concerns inherent in interdisciplinary research spanning social science and computational domains [21]. The validation approach employs methodological triangulation combining theoretical analysis, empirical case studies, and expert consultation to enhance result reliability and validity. Multiple analytical perspectives are systematically compared to identify convergent findings and resolve discrepancies through additional investigation [22].

3. Results and Discussion

3.1 Traditional Methodology Constraints and Big Data Integration Mechanisms

The systematic assessment reveals that traditional social science methodologies face fundamental limitations that extend far beyond simple computational capacity constraints. These limitations reflect deeper structural misalignments between conventional research approaches and the complexity, scale, and temporal dynamics characteristic of contemporary digital society. Traditional methodologies, designed for relatively stable social environments with limited data availability, prove inadequate for analyzing complex adaptive systems where individual behaviors aggregate to create emergent collective phenomena through digital mediation.

The most significant constraint identified involves the inability of traditional approaches to model multi-level, interconnected social phenomena. Survey-based methodologies, while effective for capturing individual attitudes and behaviors, cannot adequately represent the network effects, feedback loops, and cascading dynamics that characterize digitally-mediated social systems. For instance, understanding how individual social media behaviors aggregate to influence collective opinion formation requires analytical frameworks that can simultaneously model individual-level psychology, network-level information transmission, and system-level emergent properties. Traditional statistical approaches, predominantly designed for linear relationships and independence assumptions, fail to capture these complex interdependencies.

Data processing limitations create additional fundamental barriers. The analysis reveals that traditional methodologies can effectively handle datasets containing hundreds to low thousands of observations, while contemporary social phenomena generate datasets containing millions to billions of behavioral traces. More critically, traditional approaches focus primarily on structured, numerical data collected through controlled procedures, while digital society generates predominantly unstructured, multi-modal data including text, images, videos, audio, and behavioral traces that require sophisticated computational processing for meaningful analysis.

Big data integration addresses these limitations through several transformative mechanisms that fundamentally alter research capabilities rather than simply scaling existing approaches. Real-time data processing enables continuous monitoring of social phenomena, transforming research from retrospective analysis to

prospective observation and intervention. Multi-source data integration allows researchers to triangulate findings across different behavioral domains, reducing single-source biases while providing comprehensive perspectives on complex social phenomena. Advanced pattern recognition techniques enable discovery of latent relationships and trends that emerge from large-scale behavioral aggregation but remain invisible to traditional analytical approaches.

Table 1 presents a comprehensive comparison of traditional methodological capabilities against contemporary research requirements, revealing the magnitude of capability gaps across multiple dimensions.

Table 1. Comprehensive Methodology Comparison: Traditional Vs. Big Data Approaches in Social Science			
Research Dimension	Traditional Methodology	Big Data-Integrated Approach	Transformation Level
<i>Data Acquisition and Scope</i>			
Sample Coverage	Representative samples (n=100-5,000), geographic limitations, demographic constraints, participation bias, costly recruitment processes	Population-level data (n=millions-billions), global coverage, natural behavioral observation, reduced participation bias, automated collection systems	Radical
Data Modalities	Primarily structured surveys and interviews, limited multimedia analysis, manual transcription and coding, single-mode focus	Multi-modal integration (text, images, video, audio, behavioral traces), automated content analysis, cross-modal pattern recognition	Radical
Temporal Resolution	Discrete time points, retrospective analysis, limited longitudinal capacity, static snapshots of social phenomena	Continuous monitoring, real-time analysis, high-frequency longitudinal tracking, dynamic process observation	Radical
<i>Analytical Capabilities</i>			
Pattern Recognition	Hypothesis-driven testing, linear relationship focus, predetermined variable analysis, theory-constrained exploration	Data-driven pattern discovery, non-linear relationship detection, automated feature extraction, emergent pattern identification	Radical
Network Analysis	Small-scale relationship mapping, static network snapshots, manual relationship identification, limited connectivity analysis	Large-scale network mining, dynamic network evolution tracking, automated relationship detection, multi-layer network analysis	Radical
Predictive Modeling	Limited forecasting capability, trend extrapolation, scenario analysis, expert judgment integration	Advanced machine learning prediction, behavioral pattern forecasting, early warning systems, predictive intervention design	Significant
<i>Research Process Efficiency</i>			
Literature Synthesis	Manual literature review (50-200 sources), subjective selection, linear narrative synthesis, time-intensive analysis (3-12 months)	Automated literature analysis (1,000-100,000+ sources), objective pattern recognition, network-based synthesis, rapid processing (days-weeks)	Radical
Data Processing Speed	Sequential analysis workflows, manual quality control, batch processing, researcher-intensive procedures	Parallel processing systems, automated quality assurance, real-time analysis pipelines, algorithm-intensive procedures	Radical
Reproducibility	Manual procedure documentation, researcher-dependent replication, limited workflow standardization	Automated workflow documentation, algorithmic reproducibility, standardized processing pipelines, version-controlled analyses	Significant
<i>Knowledge Dissemination and Impact</i>			
Audience Targeting	Broad academic audience, static publication formats, limited personalization, traditional dissemination channels	Precision audience targeting, dynamic content adaptation, personalized delivery systems, multi-channel distribution	Significant
Impact Assessment	Citation-based metrics, expert evaluation, qualitative impact assessment, limited tracking capabilities	Multi-dimensional impact tracking, real-time influence monitoring, network effect analysis, automated impact assessment	Significant
Knowledge Integration	Discipline-specific knowledge silos, manual cross-reference, limited interdisciplinary synthesis	Cross-disciplinary knowledge graphs, automated concept linking, systematic interdisciplinary integration	Moderate

The transformation mechanisms extend beyond simple capability enhancement to encompass fundamental epistemological shifts in how social science research conceptualizes relationships between theory, data, and knowledge generation. Traditional deductive approaches, emphasizing hypothesis formulation followed by empirical testing, become complemented by inductive pattern discovery that generates theoretical insights through computational analysis of large-scale behavioral data. This methodological integration enables iterative research processes where computational pattern recognition generates hypotheses that undergo targeted investigation through traditional qualitative and quantitative approaches, creating more robust and comprehensive understanding of complex social phenomena.

3.2 Philosophy and Social Science Laboratory Framework Requirements

The comprehensive laboratory framework analysis reveals that successful big data integration requires institutional innovations that extend far beyond technological infrastructure acquisition. The framework encompasses seven interconnected dimensions that must be systematically addressed to achieve sustainable implementation capable of producing transformative research outcomes. These dimensions interact dynamically, creating implementation pathways where success in one area enables progress in others while deficiencies in critical areas can undermine overall laboratory effectiveness regardless of strengths in other domains.

Computational infrastructure requirements represent the most visible but not necessarily most challenging aspect of laboratory development. The analysis identifies three distinct laboratory scales with dramatically different resource requirements and capability levels. Basic laboratories, serving 5-10 researchers, require initial investments of \$135,000-\$225,000 with annual operating costs of \$150,000-\$240,000. These laboratories can support moderate-scale data analysis, standard machine learning applications, and collaborative research projects while maintaining connection to cloud computing resources for burst capacity requirements.

Intermediate laboratories, supporting 10-25 researchers, necessitate substantially higher investments of \$475,000-\$850,000 initially with annual costs of \$475,000-\$750,000, but provide distributed computing capabilities, multi-modal data processing, and advanced analytical platform integration. Advanced laboratories, designed for 25+ researchers, require initial investments exceeding \$2 million with annual operating costs of \$1-2 million, but deliver high-performance computing capabilities, comprehensive data management systems, and cutting-edge research platform development.

However, the analysis demonstrates that computational infrastructure represents only one component of successful laboratory implementation. Human capital development emerges as the most critical and challenging requirement, demanding systematic attention to recruitment, training, and retention of personnel with hybrid competencies spanning social science theory, computational methods, data management, and domain-specific application knowledge. Current academic training programs produce graduates with either strong social science backgrounds lacking computational skills or strong technical backgrounds lacking social science theoretical foundation, but rarely individuals with integrated competencies required for effective computational social science research.

3.3 Implementation Challenges and Institutional Implications

The comprehensive analysis reveals that laboratory implementation faces substantial challenges extending beyond resource acquisition to encompass fundamental institutional transformation requirements. These challenges cluster around three primary domains: resource sustainability, organizational culture adaptation, and external stakeholder coordination. The severity and nature of these challenges vary significantly across different institutional contexts, creating differentiated implementation pathways that require tailored approaches rather than universal solutions.

Resource sustainability emerges as the most persistent long-term challenge, with financial requirements that substantially exceed traditional social science research budgets. Advanced laboratory implementations require initial investments of \$2-4 million with annual operating costs of \$1-2 million, representing 10-50 times typical departmental research budgets. These resource requirements necessitate institutional-level commitment and multi-source funding strategies that combine government grants, industry partnerships, and institutional investment. The analysis of twelve international laboratory implementations reveals that successful sustainability requires diversification across 3-5 different funding sources to maintain operational stability during funding cycle transitions and economic fluctuations.

More fundamentally, the resource requirements create dependencies on external stakeholders including technology vendors, cloud computing providers, and specialized personnel markets that operate according to different timelines and priorities than traditional academic institutions. These dependencies introduce vulnerabilities and coordination challenges that require sophisticated management approaches and contingency planning. For instance, commercial cloud computing costs can fluctuate significantly based on market conditions and service provider strategies, requiring laboratories to develop flexible resource allocation strategies and alternative provider relationships.

Organizational culture adaptation presents equally significant challenges that prove more difficult to address through resource allocation alone. The integration of computational approaches within traditional social science research environments requires fundamental shifts in research conceptualization, methodological training, evaluation criteria, and collaborative practices. Traditional social science cultures emphasize individual scholarship, disciplinary expertise, and theoretical contribution, while computational social science requires collaborative teams, technical competencies, and methodological innovation. These cultural differences create tensions around resource allocation, personnel evaluation, and research priority setting that require systematic change management approaches.

The analysis identifies successful culture adaptation strategies that emphasize gradual integration rather than radical transformation. Effective laboratories develop bridge-building programs that enable traditional social scientists to acquire computational competencies while maintaining connection to disciplinary theoretical foundations. Simultaneously, these programs expose computational specialists to social science theoretical

frameworks and domain-specific knowledge requirements. This bidirectional integration approach proves more sustainable than attempting to recruit fully-formed computational social scientists or expecting rapid skill development in either direction.

External stakeholder coordination creates additional complexity layers that extend laboratory operations beyond traditional academic boundaries. Effective big data social science research requires partnerships with technology companies for platform development, government agencies for data access, industry organizations for application contexts, and international collaborations for comparative analysis. Each stakeholder relationship operates according to different timelines, objectives, intellectual property frameworks, and success criteria, requiring sophisticated coordination and negotiation capabilities.

Table 2 presents a comprehensive implementation pathway framework that addresses these multi-dimensional challenges through integrated strategic approaches.

Table 2. Philosophy and Social Science Laboratory Implementation Pathway Framework

<i>Phase I: Foundation Building and Strategic Planning</i>		
Institutional Readiness	Partnership Development	Foundation Infrastructure
<ul style="list-style-type: none"> Leadership commitment establishment and governance structure development Stakeholder analysis and engagement strategy formulation Institutional culture assessment and change management planning Resource requirement analysis and funding strategy development Risk assessment and mitigation planning 	<ul style="list-style-type: none"> Technology vendor relationship establishment and platform evaluation Academic collaboration network development and research partnership formation Industry partnership exploration and memoranda of understanding Government agency relationship development for data access International collaboration framework establishment 	<ul style="list-style-type: none"> Basic computational infrastructure procurement and installation Network and security system implementation Initial software platform acquisition and configuration Data management system design and implementation Physical space preparation and equipment installation
<i>Phase II: Capability Development and Team Building</i>		
Human Capital Acquisition	Technical Capability Building	Research Program Initiation
<ul style="list-style-type: none"> Key personnel recruitment including laboratory director and senior researchers Interdisciplinary team development and role definition Training program development and implementation Graduate student and postdoctoral fellow recruitment Administrative and technical support staff hiring 	<ul style="list-style-type: none"> Advanced computational infrastructure deployment and optimization Custom software platform development and integration Data integration system implementation and testing Security and compliance system enhancement User training and technical documentation creation 	<ul style="list-style-type: none"> Pilot research project design and implementation Methodological framework development and validation Data acquisition and processing pipeline establishment Quality assurance protocol implementation Initial research output generation and dissemination
<i>Phase III: Full Operation and Impact Generation</i>		
Research Excellence	Sustainability and Growth	Knowledge Translation
<ul style="list-style-type: none"> Large-scale research project implementation and management High-impact publication generation and dissemination Policy-relevant research and stakeholder engagement International collaboration and comparative research Innovation in computational social science methodologies 	<ul style="list-style-type: none"> Diversified funding portfolio maintenance and expansion Long-term strategic planning and capability enhancement Network expansion and collaboration deepening Technology transfer and commercialization opportunities Institutional impact and reputation building 	<ul style="list-style-type: none"> Public engagement and science communication Policy maker engagement and decision support Industry collaboration and practical application Educational outreach and capacity building Best practice dissemination and replication support

4. Conclusions

Big data integration in social science research represents a paradigmatic transformation rather than incremental technological enhancement, fundamentally altering how researchers conceptualize, investigate, and understand complex social phenomena. Traditional methodologies, designed for stable social environments with limited data availability, prove structurally inadequate for analyzing contemporary digital society's multi-level, interconnected systems where individual behaviors aggregate through technological mediation to create emergent collective dynamics.

The philosophy and social science laboratory framework address these transformation requirements through systematic integration of computational infrastructure, human capital development, data resource management, and institutional policy alignment. However, implementation demands substantial resource commitments exceeding typical social science budgets by 10-50 times, requiring institutional-level strategic planning and multi-stakeholder coordination that extends beyond traditional academic boundaries.

The analysis reveals critical implementation challenges spanning resource sustainability, organizational culture adaptation, and external partnership coordination. Success requires sustained institutional leadership, diversified funding strategies, systematic change management, and continuous adaptation to technological evolution. While basic laboratory implementations remain accessible to mid-sized institutions, advanced capabilities necessitate major institutional transformation and multi-year development timelines.

Future research must address empirical validation of laboratory effectiveness, longitudinal impact assessment, ethical framework development, and pedagogical innovation for interdisciplinary training. The convergence of big data methodologies with emerging artificial intelligence capabilities presents both unprecedented opportunities and complex challenges requiring ongoing investigation and institutional adaptation.

References

- [1] S. John Walker, "Big Data: A Revolution That Will Transform How We Live, Work, and Think," *Int J Advert*, vol. 33, no. 1, 2014, doi: 10.2501/ija-33-1-181-183.
- [2] A. G. Fallis, "The four V's of big data," *Big Data*, vol. 53, no. 9, 2013.
- [3] C. Cioffi-Revilla, "Computational social science," 2010. doi: 10.1002/wics.95.
- [4] M. J. Salganik, *Bit by bit: Social research in the digital age*. 2017. doi: 10.1177/0267323120922090.
- [5] M. Grizioti and C. Kynigos, "Integrating Computational Thinking and Data Science: The Case of Modding Classification Games," *Informatics in Education*, vol. 23, no. 1, 2024, doi: 10.15388/infedu.2024.03.
- [6] R. Kitchin, "Big Data, new epistemologies and paradigm shifts," *Big Data Soc*, vol. 1, no. 1, 2014, doi: 10.1177/2053951714528481.
- [7] D. Blei, L. Carin, and D. Dunson, "Probabilistic topic models," *IEEE Signal Process Mag*, vol. 27, no. 6, 2010, doi: 10.1109/MSP.2010.938079.
- [8] R. M. Bond *et al.*, "A 61-million-person experiment in social influence and political mobilization," *Nature*, vol. 489, no. 7415, 2012, doi: 10.1038/nature11421.
- [9] S. Lipovetsky, "Big Data and Social Science: Data Science Methods and Tools for Research and Practice," *Technometrics*, vol. 63, no. 3, 2021, doi: 10.1080/00401706.2021.1945317.
- [10] D. Trilling, "Doing Computational Social Science with Python: An Introduction," *Social Science Research Network*, 2017.
- [11] Z. Tufekci, "Big Questions for social media big data: Representativeness, validity and other methodological pitfalls," in *Proceedings of the 8th International Conference on Weblogs and Social Media, ICWSM 2014*, 2014. doi: 10.1609/icwsm.v8i1.14517.
- [12] *Frontiers in massive data analysis*. 2013. doi: 10.17226/18374.
- [13] M. Makarow, M. Zic Fuchs, and C. Moulin, "Research Infrastructures in the Digital Humanities," *Humanities*, no. September, 2011.
- [14] R. K. Yin, "Case study research: Design and methods.," *Applied Social Research Methods Series*, vol. 18, no. 2, 2013, doi: 10.1097/00001610-199503000-00004.
- [15] D. Collier, "Understanding process tracing," *PS Polit Sci Polit*, vol. 44, no. 4, 2011, doi: 10.1017/S1049096511001429.
- [16] K. A. Bollen, B. Entwisle, and A. S. Alderson, "Macrocomparative Research Methods," *Annu Rev Sociol*, vol. 19, no. 1, 1993, doi: 10.1146/annurev.so.19.080193.001541.
- [17] "Systems of innovation: Technologies, institutions and organizations," *Long Range Plann*, vol. 31, no. 2, 1998, doi: 10.1016/s0024-6301(98)90244-8.
- [18] P. Robinson, "Designing and Conducting Mixed Methods Research," *Aust N Z J Public Health*, vol. 31, no. 4, 2007, doi: 10.1111/j.1753-6405.2007.00096.x.
- [19] D. Moher *et al.*, "Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement," *Revista Espanola de Nutricion Humana y Dietetica*, vol. 20, no. 2, 2016, doi: 10.1186/2046-4053-4-1.
- [20] K. M. Eisenhardt, "Building Theories from Case Study Research," *Academy of Management Review*, vol. 14, no. 4, 1989, doi: 10.5465/amr.1989.4308385.
- [21] N. K. Denzin, *The Research Act: A Theoretical Introduction to Sociological Methods*. 2017. doi: 10.4324/9781315134543.
- [22] S. Bhangu, F. Provost, and C. Caduff, "Introduction to qualitative research methods - Part i," *Perspect Clin Res*, vol. 14, no. 1, 2023, doi: 10.4103/picr.picr_253_22.