

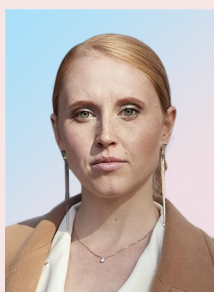
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Expanding the Toolkit for Poverty Research: An Analytical Review of Research Practices



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Abstract. This article aims to systematize the main directions in which the toolkit for poverty research is expanding and to identify how new data sources complement traditional methods, enhancing the capacity to measure, explain, and monitor various manifestations of poverty. The review draws on a multi-stage selection of Russian and international publications on poverty and a comparative analysis of these studies in terms of the instruments they employ. It focuses on both classical quantitative and qualitative tools – household surveys, official statistics, field research, and so forth – and approaches that use digital traces: mobile phone data, satellite imagery, transaction and e-commerce data, and data from online platforms. For the analysis of the classical toolkit, priority was given to the most authoritative and widely cited international and Russian publications, making it possible to reconstruct a stable methodological and instrumental core of poverty research. For the discussion of new approaches, relevant recent works on

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big data, satellite imagery, digital traces, and other data sources were included, provided they offered sufficient methodological detail. The scientific novelty of the study lies in its contribution to the ongoing debate on the use of new poverty research tools and in substantiating hybrid approaches as one of the most promising strategies for studying poverty under conditions of digital transformation and increasingly complex social inequalities. Expanding the toolkit can help improve the spatial and temporal granularity of poverty measurement, better operationalize its multidimensional aspects, and more precisely delineate vulnerable groups. The limitations of the study stem from differences in the selection procedures for the two parts of the corpus, which allow configurations of practices to be compared but do not provide grounds for broad judgments about the theoretical elaboration of the digital literature. Prospects for further research lie in applying the proposed framework to a larger corpus of publications and in empirically testing hybrid designs.

Key words: poverty, poverty concepts, poverty measurement, digital methods of poverty research, hybrid methods of poverty research, social policy.

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Introduction

Poverty is one of the most persistent and socially significant challenges of modern society, affecting not only income distribution but also access to basic public goods, human capital, social mobility, and inclusion of individuals and households in economic and social life. For Russia, which currently experiences a decline in absolute poverty, this problem is nevertheless relevant due to its large socio-economic space, regional differentiation of poverty, the complex structure of vulnerable groups, and, consequently, the possible dependence of social policy effectiveness on the accuracy of their identification (Ovcharova, 2012; Kartseva, 2020; Surinov, Luppov, 2022).

Traditional mechanisms based on official statistics and representative household surveys remain crucial for obtaining reliable and comparable estimates of the scale, depth, and socio-demographic structure of poverty (Moatsos, 2025). At the same time, their capabilities are limited when addressing the tasks of prompt and spatially

differentiated adjustment of social policy. Irregular surveys, insufficient samples for certain social groups and outlying areas, the prevalence of cross-sectional data and the dominance of the monetary approach hinder the timely identification of changes, the analysis of poverty trajectories, and the recognition of heterogeneous forms of need (Eliseeva, Raskina, 2017; Dang et al., 2019; Van der Weide et al., 2022). In this context, there is growing demand for the toolkit capable of working with constantly changing information, capturing the heterogeneity of poverty, and enabling earlier recognition of the risks of its emergence, deepening, and reproduction.

New opportunities may include the expansion of information base and introduction of digital data. Lately, researchers increasingly apply satellite imagery, mobile phone data, transaction data, digital traces, and platform data for assessing well-being, mapping poverty, identifying vulnerable groups, and improving social assistance mechanisms (Hall et al.,

2023)¹. Such approaches allow obtaining regular, spatially detailed estimates, and their practical contribution has been demonstrated in a number of empirical works based on combinations of mobile, geospatial, and algorithmic data (Steele et al., 2017; Aiken et al., 2022).

Russian research already uses some elements of the new toolkit. However, its expansion and integration into the established system of poverty research is lagging behind international practice. Russian poverty studies actively analyze absolute, relative, and multidimensional approaches (Tikhonova, 2011; Kartseva, 2020; Slobodenyuk, Mareeva, 2020; Nazarbaeva et al., 2022), whereas digital and hybrid methods are typically discussed in general scientific reviews (Markeeva, Gavrilenko, 2021; Konstantinovsky et al., 2025). Despite the growing number of works devoted to some digital sources and analytical methods, there remains a gap in research practice analysis, in understanding how modern works use new opportunities for studying poverty and how they develop traditional approaches. The article aims to classify the main directions of poverty toolkit development and to assess associated analytical opportunities and limitations. New methods are considered as supplementary to existing tools for addressing research and practical tasks of poverty alleviation policy. This article therefore attempts to answer the following question: how new methods and data sources expand the poverty research toolkit, and how does it enhance measuring, explaining, and monitoring various manifestations of poverty?

The review includes theoretical, methodological, and informational levels of research. Approaches for studying poverty represent a theoretical framework and determine the content and key manifestations of poverty; methods of collection, measurement, and analysis constitute

the research toolkit; the latter is based on data sources, or information base. Research practices are understood as the logical combination of theoretical approaches, research tools, and information base aimed at addressing some poverty issues and presented in the scientific literature. Accordingly, toolkit expansion is viewed as the development of methods of collection, measurement, and analysis associated with new data sources and ways to combine them.

Data and methods

The research design includes a scientific review in Web of Science and RSCI (eLibrary) databases based on a multi-stage search, selection, and comparative analysis of Russian and international publications from 2000 to 2025. This period allows comparing publications with traditional and modern tools developed after 2000.

At the first stage, publications were collected using queries related to poverty. The keywords were poverty and collocations related to main theoretical frameworks of poverty research: social space, social exclusion, capability approach, welfare regimes, institutional theory, co-production (Klyuev et al., 2025). We selected articles with high citation rates and developed theoretical framework published in peer-reviewed journals. At the next stage, works without a description and justification of research methods were excluded. At the full-text analysis stage, publications directly devoted to measuring poverty with an explicit description of the research method and measurement procedure were included in the final list. For the analysis of publications with traditional toolkits, priority was given to the most distinguished and cited publications, which constitute the methodological core of poverty research and represent international and Russian research fields. Using this approach, we collected a pool of 16 publications with traditional toolkits.

¹ Stubbers M., Holvoet N. Big data for poverty measurement: insights from a scoping review. IOB Discussion Papers, 2020, No. 2020.03. Antwerpen: Universiteit Antwerpen, Institute of Development Policy (IOB).

Publications that used digital toolkits for poverty research were selected in a different manner: the review included relevant recent works on big data, satellite imagery, digital traces, and other alternative data sources; the other factor was sufficient methodological description. The following keywords were used: poverty prediction, poverty estimation, poverty analysis, big data, machine learning, svm, deep learning. The main challenge at this stage was that there was no explicit list of research practices for studying poverty using digital toolkits. The main directions were therefore identified based on the studied articles which analyzed non-manually collected data. To select these publications, we estimated the transparency of data description, the logic of interpretation, and understanding of the analytical advantages and limitations of the method rather than citation indicators. Such a differentiated approach, on the one hand, relied on established approaches, and on the other, covered the new digital toolkit. In total, 22 publications with digital poverty research toolkits were selected.

In accordance with the analytical framework, publications with established research practices were selected that meet the following conditions:

- substantiated theoretical framework, methods, and information base;
- frequent occurrence of the practice among the most cited Russian and international publications; high citation rate as an indicator of scientific influence of the work; the share of publications of the corresponding practice as an indicator of its reproduction among most cited works.

For further analytical work, the dominant research practices were identified in the selected publications:

Traditional toolkit: monetary-statistical measurement; econometric modeling of factors and risks; multidimensional index measurement; institutional-

comparative analysis; qualitative study of poverty and social exclusion; analysis of public perceptions of poverty.

Digital toolkit: poverty assessment based on mobile phone data; satellite-geospatial poverty mapping; digital price and consumption data, social media and information from online platforms.

This structure avoids excessive detail while preserving the key dimensions that provide the basis for a consistent comparison of traditional and digital toolkits, identifying their advantages and limitations, and determining the possibilities for their complementarity in the Russian context.

Results

Publications with traditional toolkits were coded by dominant research practice and then classified into three groups.

1. The core – monetary-statistical and econometric practices. In the body of the most cited works, monetary-statistical and econometric practices account for 38%; their concentration is higher in the Russian sub-body – over 50% versus one-third in the international one.
2. The center – multidimensional index measurement, covering 19% of the total body of analyzed works. There are three times fewer Russian works of this kind than in the international sub-body.
3. The periphery – institutional-comparative, qualitative, and discursive practices, collectively accounting for over one-third of publications. Notably, each individual practice is represented by an equal number of works.

The results of the analysis of traditional research practices for studying poverty are presented in *Table 1*.

To sum up, traditional poverty assessment tools have played a key role in the development of poverty research. They have ensured the comparability of measurements, the reproducibility of results, and the connection between poverty analysis and the

Table 1. Established research practices for studying poverty from the most cited publications with traditional toolkits

Research practice	Theoretical framework	Main methods	Information base	Publications
Monetary-statistical dimension (1)	Monetary approach; absolute and relative poverty; welfare approach	Poverty line determination; calculation of level, depth, and dynamics; statistical comparisons	Official statistics; household budget surveys	Ovcharova, Popova, 2013; Shaidullina, Stepanova, 2020; Erokhina, Dzhergeniya, 2020
Econometric modeling of factors and risks (1)	Stratification approach; social risk theory; welfare regimes	Regression analysis; risk factor modeling; intergroup and spatial comparisons	Survey microdata; panel data; mass surveys	Lezhnina, 2010; Van Oorschot, 2006; Larsen, 2008
Multidimensional index measurement (2)	Capability approach; deprivation and resource approaches	Construction of composite indices; threshold identification; aggregation; classification	Household and special-purpose surveys; health, education, employment, and living conditions indicators	Alkire, Foster, 2011; Alkire, Santos, 2014; Rimashevskaya et al., 2013
Institutional-comparative analysis (3)	Institutional theory; precarization theory; social regimes approach	Analysis of institutions, legislation, and documents; comparative and historical analysis; case studies	Normative acts; social policy documents; historical materials; employment data	Bobkov et al., 2011; Ferraro et al., 2015; Smith et al., 2013; Lucas, 2012
Qualitative research on poverty and social exclusion (3)	Social exclusion theory; constructivist approach	In-depth interviews; monitoring; case studies; biographical and thematic analysis	Interviews; field data; life histories; monitoring data	Bayat, 2000; Mosse, 2010; Sheremet, 2022
Analysis of public perceptions of poverty (3)	Subjective and constructivist approaches; concept of deservingness of support	Mass surveys; scaling; content and discourse analysis; analysis of attitudes	Survey data; media and social policy texts; expert estimates	Mareeva, Tikhonova, 2016; Van Oorschot, 2006; Larsen, 2008
Compiled based on the analysis of selected publications.				

practice of supporting the poor. The development of the toolkit was driven by an expansion of the theoretical understanding of poverty: from income deficits to multidimensional deprivations, social risks, institutional mechanisms, and social exclusion (D'Attoma, Matteucci, 2024). In the selected works, these approaches are implemented through statistical, econometric, index-based, comparative, and qualitative methods applied to official statistics, household surveys, mass surveys, documents, and field data.

As noted earlier, the body of poverty research based on digital data was collected according to a different principle: it included all identified relevant publications that described the actual

use of digital data for studying poverty and explained the methodological procedure in detail. Therefore, this part of the review predictably included publications with varied research designs, including empirical works focused on testing data sources, building predictive models, and spatial mapping. The heterogeneity of research design required a more complex approach to assessing the conceptualization of these practices, and we identified three types of conceptualization: theoretically grounded studies, where framework determines the choice of parameters, digital features, and interpretation (1); studies with a theoretical framework in the background, where theories of poverty are

mentioned but not attached to the toolkit (2); methodologically oriented studies, where the main focus is on data (3). In total, works included in the first group accounted for 18% (4 out of 22), studies with a background theoretical framework – 32% (7 out of 22), and methodologically oriented – 59% (13 out of 22) (two publications (Geng et al., 2023; Marty, Duhaut, 2024) were included in two groups). The most pronounced methodological

orientation was found in works based on mobile data. A more explicit connection with concepts of multidimensional and spatial deprivation is typical for satellite-geospatial studies, while monetary and relative poverty is related to digital prices and consumption.

Overall, the analysis of publications revealed four practices of research based on digital data, which are presented in *Table 2*.

Table 2. Research practices for studying poverty based on digital toolkits

Digital research practice	Theoretical framework and conceptualization type	Key methods	Data	Publications
Poverty assessment based on mobile phone data (n = 7)	1 – 0%, 2 – 28,6% (2/7): monetary and resource approaches, social vulnerability; 3 – 71,4% (5/7): income, consumption, assets, or poverty status are set as an external variable	Construction of digital features; regression; machine learning; spatial prediction	Call detail records; mobility and communications; geodata; survey indicators of income, consumption, and assets	Soto et al., 2011; Frias-Martinez, Virseda, 2012; Pokhriyal, Jacques, 2017; Steele et al., 2017; Njuguna, McSharry, 2017; Aiken et al., 2022; Aiken et al., 2023
Satellite-geospatial mapping of poverty (n = 8)	1 – 25,0% (2/8): multidimensional poverty, spatial and infrastructural deprivation; 2 – 25,0% (2/8): multidimensionality and spatial heterogeneity set the context; 3 – 50,0% (4/8): satellite data are used for prediction	Computer vision; machine learning; geospatial modeling; analysis of luminosity and infrastructure	Daytime and nighttime imagery; maps of roads, land use, built-up areas, and infrastructure	Jean et al., 2016; Tingzon et al., 2019; Yeh et al., 2020; Smythe, Blumenstock, 2022; Hall et al., 2023; Nzelibe, 2024; Geng et al., 2023; Marty, Duhaut, 2024
Analysis of digital data on price and consumption (n = 3)	1 – 33,3% (1/3): relative and monetary poverty, local cost of living; 2 – 33,3% (1/3): consumption is considered an indicator of economic welfare; 3 – 33,3% (1/3): transactions are used for prediction	Local price indices; transaction analysis; construction of consumption features; predictive modeling	Price bigdata; retail chain data; e-commerce and marketplace data; income and expenditure indicators	Marchetti et al., 2024; Wijaya et al., 2022; Wijaya et al., 2024
Analysis of data from social media and digital platforms (n = 6)	1 – 16,7% (1/6): social and digital inclusion are associated with feature selection; 2 – 33,3% (2/6): social exclusion, digital inequality, and spatial heterogeneity set the context; 3 – 50,0% (3/6): platform features are considered as indirect characteristics of poverty	Construction of digital features; audience analysis; machine learning; spatial prediction; data fusion	Social media data; advertising dashboard and audience data; interests and digital presence; geoinformation; external poverty indicators	Fatehkia et al., 2020; Fatehkia et al., 2022; Giurgola et al., 2022; Ledesma et al., 2020; Geng et al., 2023; Marty, Duhaut, 2024
Compiled based on the analysis of selected publications.				

The two parts of the review therefore reveal different attitudes to research. In the highly cited body of traditional studies, practices are reconstructed through established combinations of theoretical framework, methods, and information base. In the digital body, more than half of the works are based on the methodological framework, while the theoretical framework is often expressed indirectly – through the poverty indicator used for model training or validation. The obtained distribution characterizes the composition of the selected body and should be interpreted considering differences in selection procedures between the two bodies.

Discussion

The review results show that the expansion of the poverty research toolkit is a complex and multi-level process rather than a linear one:

- the toolkit is expanding faster at the methodological and informational levels than at the theoretical level;
- there is a significant increase in methods of data collection and analysis, primarily in the area of spatial granularity and predictive modeling;
- there are breakthroughs in data and information base collection.

Notably, traditional toolkits retain a key role in defining the boundaries and content of poverty, ensuring comparability of measurements, and identifying factors of its reproduction. Digital toolkits complement them with capabilities for more detailed spatial analysis and forecasting, while the regularity of digital data generation creates prerequisites for more rapid monitoring of changes. Therefore, the main outcome of the development of the toolkit is not the replacement of one type of data by another, but the expansion of the range of research problems that can be addressed through the functional combination of theoretical approaches, methods, and information sources. This conclusion is consistent with studies showing

that monetary indicators retain their fundamental importance for measuring the scale of poverty but need to be supplemented with multidimensional characteristics to identify differences in the composition and forms of need (Eliseeva, Raskina, 2017; Kartseva, 2020). At the same time, the review results revealed inconsistency across the theoretical, methodological, and informational levels of research. In the body of most cited publications with traditional toolkits, practices are formed by established combinations of theoretical framework, methods, and information base. Digital body, however, has a different structure. Only a limited number of publications demonstrate a pronounced association between the theoretical framework and the choice of measurements, digital features, and interpretation of results. This distribution should be interpreted considering differences in selection procedures between the two bodies; however, it shows that among the reviewed works, the instrumental exploration of new data sources is developing faster than connections between theoretical frameworks of poverty, digital features, and interpretation of results. The identified asymmetry indicates a research problem of ensuring theoretically accurate operationalization of poverty in digital data. Mobile connections, satellite imagery, transactions, digital prices, and platform characteristics require coherence of the theoretical understanding of poverty, the measured manifestation, the digital feature, and the final indicator.

Another important finding of the review is the promise of hybrid designs that combine traditional and digital data sources. In analyzing the publications, we identified two interrelated dimensions of hybridization. The first characterizes the configuration of data interaction: cross-validation of estimates (Van der Weide et al., 2022), in which a poverty map based on household surveys and remote sensing data is compared with a benchmark

map combining survey and census data); mutual deepening through increased granularity (Jean et al., 2016; Yeh et al., 2020; Chi et al., 2022); and supplementation of the information base with new features (e.g., inclusion of mobile, platform, price, and transactional data capturing characteristics absent from the traditional information base (Steele et al., 2017; Fatehkia et al., 2020; Marty, Duhaut, 2024)).

In thematic terms, the spatial direction is the most developed. Satellite imagery, night-time luminosity, built-up area, road network, land use, and infrastructure data allow survey estimates to be extended to small territories and reveal intra-territorial heterogeneity of poverty (Jean et al., 2016; Yeh et al., 2020; Chi et al., 2022). The temporal direction is associated with the use of regularly generated data on prices, transactions, mobility, and digital activity. However, such sources are still predominantly used to assess the current state, while their ability to reliably reflect changes in poverty is much less confirmed (Wijaya et al., 2022; Marchetti et al., 2024; Marty, Duhaut, 2024). The behavioral direction is represented by mobile, transactional, and platform features characterizing mobility, communications, consumer activity, and digital inclusion of the population (Pokhriyal, Jacques, 2017; Steele et al., 2017; Fatehkia et al., 2020; Aiken et al., 2022). These data expand the observable space of poverty, but in most works they are used to predict an external indicator rather than to explain behavior and strategies of the population.

Thus, hybridization develops unevenly: mutual deepening and spatial granularity are most consistently represented; behavioral supplementation has already formed as an empirical direction but remains weakly integrated into poverty theory; temporal hybridization has not yet formed a stable practice for studying dynamics and trajectories.

Therefore, the significance of a hybrid design is determined not by the number of data sources combined, but by their functions, thematic content, and connection to the overall theoretical framework.

Overall, the comparison of research practices shows that the evolution of poverty research methods does not reduce to a sequential replacement of one dominant approach by another. On the contrary, there is a layering of research strategies, in which new methods do not displace old ones but compensate for their limitations and expand the analytical toolkit.

The review results allow for an improved understanding of the process of developing research practices in terms of rapidly identifying changes in the situation of specific population categories and territories. The demand from social policy for a research toolkit capable of working with dynamically updated information, capturing the heterogeneity of poverty, and providing early recognition of the risks of its emergence, deepening, and reproduction, noted above, is generally supported, as the review materials show (Aiken et al., 2022; Marty, Duhaut, 2024). At the same time, it should be noted that new data cannot automatically be transformed into policy decisions and should be used primarily as poverty monitoring tools: for preliminary diagnostics, territorial profiling, and selection of objects for in-depth research. This approach makes it possible to overcome the limited monitoring potential of traditional research practices, due to their dependence on the periodicity of surveys, statistical updates, and data availability. Digital data, including mobile communications and other digital footprints, provide greater opportunities for poverty monitoring, as they enable rapid and spatially granular estimates.

Deepening the analysis of the review results shows that the development of research practices leads to a distinction between measurement and

monitoring, since for the latter it is necessary to demonstrate the temporal stability of features, account for changes in user behavior, platform composition, data generation algorithms, and digital infrastructure. A change in a digital feature may reflect both a transformation of material conditions and a change in technology or service usage practices. In this context, the conducted review allows us to identify a new major research problem – the use of new data for studying dynamics and improving poverty reduction policy.

Thus, the generalization of the obtained data allows us to conclude that it is advisable to move from a competitive logic of comparing methods to a logic of their functional complementarity. For contemporary poverty research, what becomes fundamentally important is not the search for a single universal tool, but the construction of analytical combinations that are simultaneously sensitive to the multidimensional nature of poverty, explain the mechanisms of its reproduction, provide regular monitoring, and remain institutionally applicable in social policy practice.

Conclusion

The conducted review systematizes established and emerging research practices for studying poverty and identifies the main directions of expansion of its toolkit. The findings show that its development is driven by the expansion of methods and the information base, complication of research tasks, and gradual shift to hybrid designs.

We contributed to the analysis of poverty research by proposing the approach to assessing interconnectedness of the theoretical framework, methods, and information base. This approach assesses the research design in its integrity rather than by separate elements. Its application showed that the rapid adoption of digital sources and methods is not always accompanied by a comparable

development of their theoretical justification.

The review clarifies the problematic area of contemporary poverty research and identifies underdeveloped aspects. The first is theoretically grounded operationalization of poverty in digital data and how to ensure it. The second aspect is the challenges of using new data to study poverty trends and improve poverty reduction policy. Regular digital data generation may provide more frequent observations, but still requires additional tests proving its suitability for monitoring.

The article contributes to the discussion of the potential of digital toolkits for solving practical and managerial issues. It can provide reliable operational monitoring, individual poverty trajectories, personalized social support, improved quality of decision-making – but it requires further research, including in the area of hybridization of methods and data. A two-dimensional systematization of data hybridization in poverty research is proposed. First dimension includes identified ways of interaction between traditional and digital sources – cross-validation, mutual deepening, and supplementation; second dimension is based on the type of added information and includes spatial, temporal, and behavioral directions. The proposed classification does not claim to be exhaustive but covers the main directions of development of hybrid research designs and levels of their representation in the reviewed body of research. The findings have a number of limitations. The two parts of the review were formed according to different principles: the body of established practices included predominantly the most cited publications, while the digital body was focused on actual application of new data. Therefore, their comparison identifies differences in the composition of research practices but does not provide evidence that digital literature is in general theoretically weaker than traditional one.

Prospects for further research are associated primarily with the development of the proposed analytical framework and its application to a broader range of publications based on a unified selection and coding procedure. This will enhance assessment of the relationship between theoretical approaches, methods, and data sources in different types of poverty research.

The second direction involves the development and testing of hybrid designs. In them, traditional

toolkits should provide definition and external validation of poverty, digital data – territorial granularity and additional features, and qualitative methods – substantive explanation of mechanisms and population strategies. Their advantage should be confirmed by comparison not only of predictive accuracy but also of temporal stability, interpretability, cost, coverage of vulnerable groups, and suitability for specific managerial tasks.

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