

MODELLING AND FORECASTING POVERTY: A COMPREHENSIVE REVIEW OF INDICATORS, VULNERABILITY FRAMEWORKS, AND ANALYTICAL APPROACHES

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TABLE OF CONTENTS

SUMMARY	1
POVZETEK	3
INTRODUCTION	5
1 BROAD-BASED POVERTY	9
1.1 Concept and indicators.....	9
1.2 Modelling approaches to poverty identification	10
1.3 Forecasting approaches to broad-based poverty and key predictive variables.....	12
2 ENERGY POVERTY	15
2.1 Concept and indicators.....	15
2.2 Modelling approaches to energy poverty.....	20
2.3 Forecasting energy poverty and key predictive variables.....	24
3 TRANSPORT POVERTY	29
3.1 Concept and indicators.....	29
3.2 Modelling approaches to transport poverty	33
3.3 Forecasting transport poverty and key predictive variables	36
4 HOUSING POVERTY	39
4.1 Concept and indicators.....	39
4.2 Modelling and forecasting housing poverty	41
5 WATER POVERTY	45
5.1 Concept and indicators.....	45
5.2 Modelling and forecasting water poverty	46
6 FOOD POVERTY	49
6.1 Concept and indicators.....	49
6.2 Modelling and forecasting food poverty.....	49



7	DIGITAL POVERTY	51
7.1	Concept and indicators.....	51
7.2	Modelling and forecasting digital poverty.....	52
8	CONCLUSION	55
	REFERENCES.....	63

List of abbreviations

2M – Energy expenditure share exceeding twice the national median

AF – Alkire–Foster methodology

ARIMA – Autoregressive integrated moving average

EPAH – Energy Poverty Advisory Hub

EU – European Union

EU-SILC – European Union Statistics on Income and Living Conditions

FAO – Food and Agriculture Organization of the United Nations

FIES – Food Insecurity Experience Scale

GDP – Gross domestic product

GIS – Geographic information system

ILO – International Labour Organization

JRC-GEM-E3 – Joint Research Centre General Equilibrium Model for Economy–Energy–Environment

LIHC – Low Income High Costs indicator

M/2 – Absolute energy expenditure below half the national median

MPI – Multidimensional Poverty Index

OECD – Organisation for Economic Co-operation and Development

SHAP – SHapley Additive exPlanations

UK – United Kingdom

UN – United Nations

UN DESA – United Nations Department of Economic and Social Affairs

UNDP – United Nations Development Programme

UN-Habitat – United Nations Human Settlements Programme

UN-Water – United Nations inter-agency coordination mechanism for freshwater-related issues, including sanitation

US – United States

VEP – Vulnerability as Expected Poverty

WHO – World Health Organization

WPI – Water Poverty Index



SUMMARY

Poverty is increasingly understood as a multidimensional and dynamic condition that cannot be adequately described by income alone. Individuals and households may also experience inadequate access to housing, energy, mobility, water, food and digital technologies. Although these forms of deprivation are interconnected, each has distinct definitions, indicators, mechanisms and data requirements. This monograph comparatively reviews broad-based poverty and six domain-specific forms, i.e. energy, transport, housing, water, food and digital poverty, with emphasis on their conceptualisation, measurement, modelling and forecasting.

The monograph adopts a structured critical-review approach, combining foundational studies, representative empirical applications and authoritative institutional sources. The literature is examined through a common analytical framework covering definitions and indicators, modelling approaches, forward-looking applications and relevant explanatory or predictive variables. Particular attention is paid to distinguishing observed poverty from vulnerability to future deprivation and to separating measurement, explanatory modelling, conditional projection and genuine statistical forecasting.

The review confirms that no single indicator simultaneously captures all relevant angles of poverty. Monetary indicators measure affordability pressures but may overlook households that reduce or forego essential consumption. Subjective indicators capture experienced hardship but depend partly on expectations, adaptation and survey design. Infrastructural and spatial indicators identify deficiencies in availability and physical access, while composite indices capture overlapping disadvantages but remain sensitive to selected dimensions, thresholds, weights and aggregation methods. Indicator choice therefore affects which households, groups or places are recognised as deprived and prioritised by policy.

The reviewed methods range from regression and multidimensional counting models to spatial analysis, longitudinal models, microsimulation, agent-based modelling and machine learning. Cross-sectional approaches identify current deprivation and its correlates, while longitudinal models examine persistence and movements into and out of poverty. Microsimulation and structural models estimate conditional effects of changes in prices, policies, technologies or



environmental conditions. Genuine forecasting, by contrast, requires predictions based on information available at the time and validation against observations not used in model development.

The development of forward-looking analysis varies considerably across domains. Broad-based poverty has the most established vulnerability models, while energy-poverty forecasting is emerging through panel, climate-informed and scenario applications. Transport research primarily uses accessibility and land-use models for scenario assessment. Housing-market forecasting is comparatively mature, but forecasts are rarely translated into household-level housing poverty. Water and food research offers advanced environmental, market and early-warning models, although links to household deprivation remain incomplete. Digital-poverty forecasting is the least developed and focuses mainly on infrastructure deployment and technology adoption.

Several common explanatory and predictive factors nevertheless emerge: income, employment, demographic characteristics, health, prices, housing conditions, infrastructure, spatial location, climate, technology, social protection and public policy. Their interactions become especially important when households face simultaneous economic shocks. Rising energy prices, for example, can affect heating, mobility, food costs and housing affordability, while residential location shapes access to employment, transport, digital connectivity and essential services. Such relationships can generate cumulative and cascading forms of deprivation.

The monograph concludes that these interdependencies do not justify replacing domain-specific analysis with a universal poverty measure. A more appropriate framework is modular, preserving separate outcomes for each domain while linking them through shared household, macroeconomic, spatial and environmental factors. Future research requires integrated longitudinal data, transparent treatment of uncertainty, sensitivity analysis and genuine out-of-sample validation. Forward-looking models can complement current poverty indicators by identifying households or areas that may become deprived following changes in income, prices, infrastructure, climate or policy. By connecting analytical traditions that have largely developed separately, the monograph provides a comparative foundation for anticipating emerging deprivation and designing more preventive, coordinated and distributionally informed policies.

POVZETEK

Revščina se vse pogosteje razume kot večdimenzionalno in dinamično stanje, ki ga ni mogoče ustrezno opredeliti zgolj z dohodkom. Posamezniki in gospodinjstva se lahko soočajo tudi z nezadostnim dostopom do stanovanj, energije, mobilnosti, vode, hrane in digitalnih tehnologij. Čeprav so te oblike pomanjkanja medsebojno povezane, ima vsaka svoje opredelitve, kazalnike, mehanizme in podatkovne zahteve. Monografija primerjalno obravnava splošno revščino in šest področno specifičnih oblik revščine – energetska, prevozno, stanovanjsko, prehransko, digitalno revščino ter revščino, ki je povezana z oskrbo z vodo, s poudarkom na njihovi konceptualizaciji, merjenju, modeliranju in napovedovanju.

Monografija temelji na strukturiranem kritičnem pregledu, ki združuje temeljne študije, reprezentativne empirične raziskave in verodostojne institucionalne vire. Pregled literature temelji na skupnem analitičnem okviru, ki vključuje opredelitve in kazalnike, pristope k modeliranju, analize prihodnjega razvoja ter relevantne pojasnjevalne in napovedne spremenljivke. Posebna pozornost je namenjena razlikovanju med trenutnim stanjem revščine in tveganjem, da bi se le-ta pojavila v prihodnosti, ter razmejitvi med merjenjem, pojasnjevalnim modeliranjem, pogojnimi projekcijami in dejanskim statističnim napovedovanjem.

Pregled potrjuje, da noben posamezen kazalnik ne zajame vseh relevantnih pojavnih oblik revščine. Monetarni kazalniki merijo pritiske na cenovno dostopnost, vendar lahko spregledajo gospodinjstva, ki omejujejo ali se odpovedujejo nujni potrošnji. Subjektivni kazalniki zajemajo izkušnje pomanjkanja, vendar so deloma odvisni od pričakovanj, prilagajanja in zasnove anket. Infrastrukturni in prostorski kazalniki razkrivajo pomanjkljivosti v razpoložljivosti in fizični dostopnosti, medtem ko sestavljeni kazalniki zajemajo prekrivajoče se prikrajšanosti, vendar so občutljivi na izbiro dimenzij, pragov, uteži in metod agregiranja. Izbiira kazalnikov zato vpliva na to, katera gospodinjstva, skupine ali območja so prepoznana kot prikrajšana in prednostno obravnavana v okviru politik.

Pregledane analitične metode obsegajo regresijske modele in metode večdimenzionalnega merjenja revščine, prostorske analize, longitudinalne modele, mikrosimulacije, modelske pristope na podlagi agentov in strojno učenje. Presečne analize opredeljujejo trenutno pomanjkanje in povezane spremenljivke,

longitudinalni modeli pa analizirajo vztrajnost revščine ter prehode v in iz nje. Mikrosimulacijski in strukturni modeli ocenjujejo pogojne učinke sprememb cen, politik, tehnologij ali okoljskih razmer. Dejansko napovedovanje pa zahteva napovedi, ki temeljijo na informacijah, razpoložljivih v času napovedi, ter njihovo preverjanje z opazovanji, ki niso bila uporabljena pri razvoju modela.

Razvitost analiz prihodnjega razvoja se med posameznimi področji precej razlikuje. Pri splošni revščini so najbolj uveljavljeni modeli ranljivosti, medtem ko se napovedovanje, na primer, energetske revščine razvija z uporabo panelnih in podnebno podprtih modelov ter analize scenarijev. Raziskave prevozne revščine za ocene scenarijev uporabljajo predvsem modele dostopnosti in rabe prostora. Napovedovanje stanovanjskega trga je razmeroma razvito, vendar se napovedi le redko neposredno pretvorijo v ocene stanovanjske revščine na ravni gospodinjstev. Raziskave prehranske revščine in revščine, ki je povezana z oskrbo vode, uporabljajo napredne okoljske in tržne modele ter sisteme zgodnjega opozarjanja, vendar je njihova povezava s pomanjkanjem gospodinjstev pogosto nepopolna. Napovedovanje digitalne revščine je najmanj razvito in se osredotoča predvsem na širjenje infrastrukture ter sprejemanje tehnologij.

Kljub razlikam se pojavlja več skupnih pojasnjevalnih in napovednih dejavnikov: dohodek, zaposlenost, demografske značilnosti, zdravje, cene, stanovanjske razmere, infrastruktura, prostorska lokacija, podnebje, tehnologija, socialna zaščita in javne politike. Njihove medsebojne povezave postanejo še posebej pomembne, kadar se gospodinjstva sočasno soočajo z več ekonomskimi šoki. Rast cen energije lahko, na primer, vpliva na ogrevanje, mobilnost, stroške hrane in stanovanjsko dostopnost, medtem ko kraj bivanja določa dostop do zaposlitve, prevoza, digitalne povezanosti in osnovnih storitev.

Monografija ugotavlja, da te medsebojne odvisnosti ne upravičujejo nadomestitve področno specifičnih analiz z univerzalnim kazalnikom revščine. Primernejši je modularen okvir, ki ohranja ločene izide za posamezna področja revščine, hkrati pa jih povezuje prek skupnih značilnosti gospodinjstev ter makroekonomskih, prostorskih in okoljskih dejavnikov. Prihodnje raziskave zahtevajo povezane longitudinalne podatke, pregledno obravnavo negotovosti, analize občutljivosti in dejansko zunajvzorčno preverjanje napovedi. V prihodnost usmerjeni modeli lahko dopolnijo obstoječe kazalnike revščine z ugotavljanjem, katera gospodinjstva ali območja bi lahko postala prikrajšana zaradi sprememb dohodkov, cen, infrastrukture, podnebja ali politik.

INTRODUCTION

Poverty is increasingly understood not as a single condition defined exclusively by insufficient income, but as a multidimensional and dynamic form of deprivation. Monetary resources remain fundamental, yet they do not fully determine whether individuals and households can secure adequate housing, energy, mobility, water, food, digital connectivity and participation in society. The shift from income-based definitions towards relative, capability-based and multidimensional approaches has therefore broadened both the substantive meaning of poverty and the methods used to measure it (Townsend, 1979; Sen, 1999; Alkire & Foster, 2011). It has also highlighted that poverty may change over time: households can enter, remain in or escape deprivation as their resources, needs, exposure to shocks and access to public and private services evolve.

Different forms of poverty are related, but they are not interchangeable. Broad-based poverty provides the wider socioeconomic context within which more specific forms of deprivation emerge. Energy poverty concerns access to adequate domestic energy services; transport poverty concerns the affordability and accessibility of necessary mobility; housing poverty concerns access to affordable, secure and adequate accommodation; water and food poverty relate to the reliable provision of essential material needs; and digital poverty concerns the ability to access and effectively use technologies that have become increasingly important for employment, education, healthcare and public services. Each domain has its own conceptual boundaries, indicators, data requirements and mechanisms. At the same time, they share important determinants, including household income, prices, employment, demographic characteristics, infrastructure, spatial location, institutional arrangements and social protection. Deprivation in one domain may also intensify deprivation in another, for example, high housing costs can constrain expenditure on energy and food, while inadequate transport or digital access can limit employment opportunities and access to essential services.

These connections become particularly important when households are exposed to overlapping economic, environmental, technological and institutional changes. Inflation, energy- and food-price shocks, climate-related hazards, demographic change, infrastructure disruption and policy reforms can affect several dimensions of household welfare simultaneously. Their effects may accumulate through



common pressures, cascading consequences and feedback mechanisms rather than remaining confined to a single sector (Lawrence et al., 2024). Analysing each poverty domain separately is therefore necessary for identifying its specific mechanisms, but insufficient for understanding how deprivation develops within a wider socioeconomic system.

This perspective also requires a clear distinction between measurement, modelling and forecasting. Indicators identify the presence or intensity of an observed deprivation, whereas explanatory models estimate relationships between poverty outcomes and their possible determinants. Longitudinal models analyse persistence and transitions over time, while microsimulation and scenario-based approaches estimate conditional outcomes under specified changes in prices, policies, technologies or environmental conditions. Statistical forecasting, in a narrower sense, seeks to predict future values or statuses using information available at the time of prediction and should be evaluated through out-of-sample performance. These approaches answer different questions and should not be treated as methodologically equivalent. The same distinction applies to the concepts of poverty, vulnerability, risk and resilience. In this monograph, poverty or deprivation denotes an observed condition; vulnerability refers to a household's susceptibility to future deprivation; risk incorporates both the likelihood and potential consequences of an adverse outcome; and resilience or adaptive capacity refers to the ability to prevent, absorb, adapt to or recover from shocks. Vulnerability-oriented research consequently shifts the analytical focus from identifying who is currently poor towards assessing who may become poor under future conditions (Hoddinott & Quisumbing, 2010).

Against this background, the monograph addresses three overarching questions. First, how are broad-based poverty and selected domain-specific forms of poverty conceptualised and measured, and what are the principal strengths and limitations of the available indicators? Second, which analytical approaches have been used to identify poverty, explain its determinants and examine its spatial and temporal dynamics? Third, to what extent have these approaches been extended towards genuine forecasting, conditional projection or scenario analysis, and which variables may credibly be incorporated in forward-looking models? By applying these questions across several fields, the monograph identifies both shared methodological challenges and domain-specific requirements. Its contribution lies in bringing together bodies of literature that

have largely developed separately and evaluating what their concepts, data and methods can contribute to a broader understanding of poverty modelling and forecasting.

The monograph adopts a structured critical review. Its comprehensive character refers to the breadth of poverty domains and analytical approaches considered, rather than to an assertion that every relevant publication has been identified through a formal systematic-review protocol. The review combines foundational conceptual and methodological contributions, representative empirical applications and authoritative institutional sources. Although particular attention is given to European evidence where comparable household and policy data are available, studies from other contexts are included when they introduced an influential concept, indicator or modelling approach. Across the chapters, the literature is organised according to a common analytical sequence: definition and indicators, modelling approaches, forecasting or scenario-based applications, and relevant explanatory or predictive variables. Particular attention is paid to the distinction between observed associations, causal interpretation, conditional simulations and validated predictions.

The remainder of the monograph follows this comparative structure. Chapter 2 establishes the conceptual and methodological foundations through broad-based poverty, covering monetary, material, subjective and multidimensional indicators, models of poverty identification and dynamics, and vulnerability-oriented forecasting. Chapter 3 examines energy poverty; Chapter 4 addresses transport poverty; and Chapter 5 considers housing poverty. Chapters 6, 7 and 8 then review water, food and digital poverty, respectively. Within each domain, the discussion considers how deprivation is defined and measured, which modelling approaches have been applied, what forward-looking methods are available and which variables may be relevant for explaining or anticipating future developments. Differences in the length and methodological depth of the chapters reflect differences in the maturity and availability of the corresponding literature rather than a hierarchy among the poverty domains.

The central proposition of the monograph is therefore that credible poverty modelling and forecasting must be both domain-sensitive and methodologically plural. No single indicator captures every relevant form of deprivation, and no single modelling approach is appropriate for every analytical or policy purpose.



Comparability requires a common framework, but meaningful analysis also requires the specific mechanisms, data limitations and institutional settings of each poverty domain to be preserved. A cross-domain perspective can consequently support more transparent model selection, reveal opportunities for methodological learning between fields and contribute to forward-looking policies that identify emerging deprivation before it becomes persistent.

1 BROAD-BASED POVERTY

1.1 Concept and indicators

Poverty refers to a condition in which individuals or households lack the material, financial and social resources necessary to attain a minimally acceptable standard of living in the society in which they live (Townsend, 1979; Sen, 1999; Ravallion, 1998). Although early definitions framed poverty largely in terms of income or consumption shortfalls, contemporary socio-economic literature increasingly understands poverty as a multidimensional phenomenon, encompassing deprivations in health, education, housing, employment security, nutrition, political participation and social inclusion (UNDP, 2010; Alkire & Foster, 2011). There is broad consensus that poverty is structurally embedded, spatially uneven and temporally dynamic, changing over the life course and in response to macroeconomic, institutional and environmental transformations (Hulme & Shepherd, 2003; Thorbecke, 2013).

Poverty is widely recognised as a complex condition that cannot be adequately captured by a single indicator. As a result, poverty indicators are commonly grouped into three broad categories:

- Income and consumption-based indicators,
- Asset and material deprivation indicators, and
- Subjective or perception-based indicators reflecting experienced hardship and social norms.

Traditional income-based approaches define poverty using absolute or relative poverty lines, such as international extreme poverty thresholds or national relative poverty measures based on median incomes. The most widely used quantitative measures include the headcount ratio, which captures the proportion of the population below the poverty line, and the poverty gap and severity indices, which estimate the depth and inequality of poverty (Foster, Greer & Thorbecke, 1984). These approaches offer simplicity, transparency and cross-country comparability. However, they suffer from well-documented limitations: they fail to reflect intra-household inequalities, non-monetary deprivation and socially constructed dimensions of poverty and are insensitive to the structural causes of disadvantage.



Material deprivation and asset-based indicators were developed to complement purely monetary measures. These indicators assess households' lack of basic durable goods, housing conditions, access to utilities and capacity to participate in customary social activities. In the European context, the current EU-SILC material and social deprivation framework considers the enforced lack of household- and individual-level items such as the ability to keep the home adequately warm, afford a meal containing meat, chicken, fish or a vegetarian equivalent every second day, face unexpected expenses, access a car or van for personal use, replace worn-out furniture or clothing, maintain an internet connection and participate in customary leisure and social activities (Eurostat, n.d.-a). While more closely aligned with lived experience, these indicators depend heavily on context-specific social norms and may not be fully comparable across societies with different consumption standards.

Subjective poverty indicators rely on self-assessments of financial strain, social exclusion and perceived living standards. Questions from Eurostat, such as the difficulty of "making ends meet" or feeling poor relative to others capture relational aspects of deprivation that escape monetary and asset-based frameworks. These indicators are sensitive to cultural expectations and adaptive preferences and therefore introduce potential bias, but they provide valuable insights into social inclusion and psychological dimensions of poverty that are otherwise unobservable.

1.2 Modelling approaches to poverty identification

Modelling traditions in poverty research have broadened from static, cross-sectional measurements towards dynamic, multidimensional and vulnerability-oriented frameworks (Baulch & Hoddinott, 2000; Hulme & Shepherd, 2003; Alkire & Foster, 2011; Dercon, 2005). Early poverty analysis was dominated by unidimensional income-based measurement frameworks grounded in welfare and poverty-line analysis (Foster, Greer & Thorbecke, 1984; Atkinson, 1987; Ravallion, 1992, 1998). Cross-sectional empirical studies also commonly used regression-based techniques to relate poverty status to observable household characteristics such as education, family size and employment status. Other contributions focused on the incidence, intensity and inequality of poverty (Jenkins & Lambert, 1997) or used longitudinal data to analyse poverty spells and

transitions into and out of poverty (Bane & Ellwood, 1986). Because cross-sectional approaches cannot distinguish persistent from transient poverty, subsequent work increasingly employed longitudinal and vulnerability-oriented frameworks to examine poverty dynamics and future risk (Jalan & Ravallion, 2000; Dercon, 2005).

The introduction of the Alkire–Foster (AF thereafter) methodology marked a significant paradigmatic shift in poverty analysis. This framework measures poverty across multiple deprivations, commonly relating to health, education and living standards, by applying one set of cut-offs to determine deprivation in each indicator and a second cut-off to identify individuals or households as multidimensionally poor (Alkire & Foster, 2011). The AF approach captures not only the incidence of poverty but also its intensity, thereby accounting for overlapping disadvantages that income-only measures may not directly reveal (Alkire & Santos, 2010; Alkire & Foster, 2011). Building on this foundation, the framework has been operationalised globally through the Multidimensional Poverty Index (MPI thereafter) (Alkire & Santos, 2010; UNDP, 2010) and subsequently adapted to national and regional contexts across low-, middle- and high-income countries (Roche, 2013; Santos et al., 2015; Alkire et al., 2015).

Alongside multidimensional counting approaches, latent-class, principal-component and fuzzy-set methods have been used to construct poverty-related measures from multiple observed indicators. Latent-class analysis allows economically vulnerable groups to be identified probabilistically and produces estimated class-membership probabilities (Whelan & Maître, 2010). Principal-component methods instead construct continuous socioeconomic-status scores from correlated asset and other proxy variables (Kolenikov & Angeles, 2009), while fuzzy-set approaches assign households degrees of poverty membership rather than classifying them as simply poor or non-poor (Betti et al., 2020; Primc, Slabe-Erker & Majcen, 2019). Although all these approaches move beyond a single binary income-poverty indicator, they represent conceptually and methodologically distinct forms of measurement.

Dynamic poverty models use longitudinal data to differentiate chronic poverty from transient poverty and to capture movements into and out of deprivation over time (Baulch & Hoddinott, 2000; Hulme & Shepherd, 2003; Jalan & Ravallion, 2000). Hazard and spell-duration approaches estimate the probabilities of exiting,



entering or re-entering poverty and examine the duration and recurrence of poverty spells (Bane & Ellwood, 1986; Stevens, 1994, 1999). First-order Markov transition models can also be used to analyse low-income entry, persistence and exit while accounting for initial conditions and state dependence (Cappellari & Jenkins, 2004), while event-based longitudinal analyses relate poverty transitions to changes in employment, earnings and household composition (Jenkins & Rigg, 2001). Together, these approaches demonstrate substantial persistence in poverty dynamics and suggest that poverty can become self-reinforcing where households possess limited assets, have weak mechanisms for managing risk and face repeated exposure to shocks (Dercon, 2005; Carter & Barrett, 2006).

1.3 Forecasting approaches to broad-based poverty and key predictive variables

Forecasting poverty, as an extension of the modelling framework, increasingly draws on vulnerability-oriented approaches that shift attention from current poverty to the risk of future poverty (Christiaensen & Subbarao, 2005; Dercon, 2005; Hoddinott & Quisumbing, 2010). One prominent approach is the vulnerability-as-expected-poverty (VEP) framework, which defines vulnerability as the conditional probability that a household's future income or consumption will fall below a specified poverty line (Pritchett, Suryahadi & Sumarto, 2000; Chaudhuri, Jalan & Suryahadi, 2002). Standard implementations estimate the conditional mean and variance of household income or consumption and, under an assumed distribution, calculate the probability of falling below the poverty line (Chaudhuri, Jalan & Suryahadi, 2002; Günther & Harttgen, 2009). More flexible extensions can model additional parameters of the conditional income distribution and evaluate the predictive performance of vulnerability classifications (Hohberg et al., 2018). VEP should be distinguished from expected-utility approaches, which assess welfare losses arising from poverty and exposure to uncertainty rather than directly estimating the probability of crossing a poverty line (Ligon & Schechter, 2003).

Key explanatory variables and potential predictors used in poverty modelling and forecasting include:

- Labour market conditions, such as unemployment, informal employment, contract insecurity and sectoral employment patterns (Fields, 2011; Bosch, Goni & Maloney, 2007; Kapsos, 2005);
- Macroeconomic conditions, including GDP growth and volatility, inflation, wage developments and fiscal conditions (Ravallion, 2001, 2016; Ferreira et al., 2010; Loayza & Raddatz, 2010; Mahler, Castañeda Aguilar & Newhouse, 2022);
- Educational attainment and skills, which shape long-term earning capacity and resilience to labour-market changes (Schultz, 1961; Psacharopoulos & Patrinos, 2004; Glewwe, 2002);
- Household demographic structure, including household size, dependency ratios, single parenthood and population ageing (Lanjouw & Ravallion, 1995; Woolard & Klasen, 2005);
- Health risks and disability, which can reduce earning capacity and increase household expenditure needs (Strauss & Thomas, 1998; Wagstaff, 2002; Deaton, 2003; Mitra, Posarac & Vick, 2013);
- Asset ownership, savings and access to credit, which provide buffers against shocks and transitory poverty (Carter & Barrett, 2006; Dercon, 2005; Zeller & Sharma, 1998);
- Institutional characteristics, particularly the coverage and adequacy of social protection systems and cash-transfer programmes (Barrientos & Hulme, 2009; Fiszbein & Schady, 2009; ILO, 2024);
- Spatial characteristics, including regional labour demand, urban–rural disparities, neighbourhood effects and transport accessibility, which shape access to employment, services and economic opportunities (Elbers, Lanjouw & Lanjouw, 2003; Kanbur & Venables, 2005; Jalan & Ravallion, 2002; Zabavnik et al., 2025);
- Environmental and climate risks, increasingly incorporated to capture livelihood sensitivity to droughts, floods, heatwaves and other climate-related shocks (Dercon, 2004; Hertel & Rosch, 2010; Hallegatte & Rozenberg, 2017).

Taken together, these modelling and forecasting approaches treat broad-based poverty as a dynamic condition rather than a static status and conceptualise



vulnerability as the risk of entering or remaining in poverty. Both are shaped by interacting economic, demographic, institutional and environmental processes, whose effects may compound when crises overlap (Lawrence et al., 2024). Building on this foundation, the remainder of the monograph examines energy poverty and transport poverty, followed by other domain-specific forms of deprivation, including housing, water, food and digital poverty, to assess how modelling and forecasting approaches have developed across these interrelated dimensions.

2 ENERGY POVERTY

2.1 Concept and indicators

Energy poverty refers to a household's lack of access to essential energy services at levels needed to support a basic and decent standard of living, whether because such services are unavailable, unaffordable or otherwise inaccessible (Bouzarovski & Petrova, 2015; Day et al., 2016; González-Eguino, 2015; European Parliament & Council of the European Union, 2023a). It is a complex and multidimensional condition whose prevalence and drivers vary over time and across countries, regions, neighbourhoods, buildings and household groups. Differences in data availability, housing stocks, climates, energy systems and welfare arrangements further complicate its measurement and cross-national comparison (Thomson et al., 2017; Bardazzi et al., 2023; Lieth et al., 2025). Research has consequently developed multidimensional measurement and spatial-vulnerability frameworks (Castaño-Rosa et al., 2019; Kashour & Jaber, 2024; Lieth et al., 2025), alongside a smaller emerging literature on formal forecasting and predictive frameworks (Carfora, Scandurra & Thomas, 2022; Mochida, Chapman & McLellan, 2025). Although Directive (EU) 2023/1791 now provides a common EU-level legal definition, Member States continue to differ in how energy poverty is operationalised, measured and addressed, reflecting national housing, climate, welfare and energy-market contexts (European Commission, 2024).

Energy poverty cannot be adequately represented by a single universally accepted indicator, because alternative measures capture different dimensions and frequently identify different households as energy poor (Deller, 2018; Ntaintasis, Mirasgedis & Tourkolias, 2019; Menyhért, 2024). The literature commonly distinguishes three complementary measurement approaches (Thomson, Bouzarovski & Snell, 2017; Tirado Herrero, 2017; Campagna et al., 2024):

- Expenditure–income indicators, which compare households' actual or required energy costs with income using absolute or relative thresholds;
- Consensual or self-reported indicators, which capture households' perceived ability to obtain adequate energy services and related

experiences of deprivation, including an inability to keep the home adequately warm, arrears on utility bills and self-reported housing problems such as leaks, damp or rot; and

- Direct-measurement indicators, which compare the level of energy services achieved in the home with a specified standard, most commonly through measurements of indoor temperature.

These approaches may be used together as a basket of complementary indicators or combined into a composite index. Composite approaches reflect the multidimensional nature of energy poverty but require additional choices concerning indicator selection, weighting and aggregation (Ntaintasis, Mirasgedis & Tourkolias, 2019; Kashour & Jaber, 2024; Teixeira et al., 2024). The discussion below focuses primarily on expenditure–income and consensual indicators because these constitute the two principal approaches used in EU-level monitoring and much of the related empirical research, whereas direct measurement remains comparatively uncommon at national and European scales (Thomson, Bouzarovski & Snell, 2017; Menyhért, 2023).

Expenditure–income indicators compare household energy expenditure and income using absolute or relative thresholds. Prominent measures include the 2M, M/2 and Low Income High Costs (LIHC) indicators, alongside the earlier 10% rule developed in the UK fuel-poverty literature (Boardman, 1991; Hills, 2012; Rademaekers et al., 2016). The 2M indicator classifies a household as energy poor when the share of its income devoted to domestic energy expenditure exceeds twice the national median of that share (Rademaekers et al., 2016). Specific implementations differ in their definitions of income and expenditure and in whether equivalence scales are applied; the implementation proposed by Rademaekers et al. (2016), for example, uses equivalised disposable income. The indicator captures households facing a disproportionately high energy-cost burden, but it cannot identify hidden energy poverty where households restrict their energy use and consequently report low expenditure. Conversely, it may classify voluntary or high-income overconsumption as energy poverty unless it is combined with an income condition or complementary indicators (Campagna et al., 2024; Deller, Turner & Waddams Price, 2021).

The M/2 indicator identifies households whose absolute domestic energy expenditure is below half the national median (EPAH, 2022). It is intended to flag abnormally low expenditure and possible hidden energy poverty arising from the restriction of energy use. However, low expenditure is not in itself conclusive evidence of deprivation, as it may also reflect an energy-efficient dwelling, lower household energy needs, access to inexpensive fuels or particular billing arrangements. Moreover, because M/2 is based on a relative national threshold, its results depend on the expenditure distribution and are not directly comparable across countries (EPAH, 2022; Thomson, Bouzarovski & Snell, 2017). It should therefore be treated as a screening indicator and complemented with information on household needs, dwelling characteristics and achieved energy services (Barrella et al., 2022).

The Low Income High Costs (LIHC) indicator, developed in the English fuel-poverty context, classifies a household as fuel poor when its required or modelled energy costs exceed the contemporary national median and paying those costs would leave it with a residual income below the official poverty line (Hills, 2012). LIHC therefore combines information on income and required energy costs and permits the calculation of a fuel-poverty gap. Nevertheless, its results depend on normative and modelling choices concerning the poverty threshold, required energy services, equivalence scales and the estimation of necessary energy costs (Moore, 2012). More generally, expenditure-based indicators apply transparent threshold rules and can support monitoring over time, but they remain sensitive to data and methodological choices, while differences in climates, housing stocks, energy systems and national expenditure distributions constrain cross-national comparability (Bouzarovski, 2014; Thomson, Bouzarovski & Snell, 2017).

Self-reported, or consensual, indicators use survey responses to capture households' experienced ability to secure adequate domestic energy services and related forms of material and housing deprivation (Thomson, Bouzarovski & Snell, 2017; Petrova et al., 2013). At EU level, the principal consensual indicator derived from EU-SILC is the inability to keep the home adequately warm, generally reported as the share of people living in households that cannot keep their dwelling adequately warm. Arrears on utility bills are also widely used as a consensual energy-poverty indicator. The EU-SILC item concerning a leaking roof, damp walls, floors or foundations, or rot in window frames or floors is instead a

self-reported housing-deprivation indicator that provides complementary information on dwelling quality (Eurostat, n.d.-b). These indicators are relatively straightforward to calculate and interpret and provide insight into experienced deprivation that expenditure–income measures may not capture (Waddams Price, Brazier & Wang, 2012). The established warmth indicator does not encompass summer energy deprivation; a separate and growing literature therefore examines households' ability to maintain adequately cool indoor conditions (Thomson et al., 2019).

Perception-based indicators nevertheless have important limitations. Responses may be influenced by household expectations, social norms, temperature preferences and adaptation to prolonged deprivation; some households may normalise inadequate warmth or be reluctant to report hardship (Tirado Herrero, 2017; Deller, Turner & Waddams Price, 2021). At the same time, disagreement with an expenditure-based classification should not automatically be interpreted as reporting error, because perception-based indicators may capture household needs and lived experiences that expenditure thresholds overlook. Empirical studies show limited overlap between perception- and expenditure-based indicators and weak correlation between aggregate indices constructed from them (Deller, Turner & Waddams Price, 2021; Wojewódzka-Wiewiórska, Dudek & Ostasiewicz, 2024). Cross-country comparability is further constrained by differences in climate, building performance, heating and cooling systems, cultural understandings of comfort and, in some cases, survey wording and translation (Petrova et al., 2013; Thomson, Bouzarovski & Snell, 2017; Tirado Herrero, 2017). These limitations support triangulating perception-based indicators with expenditure data and, where feasible, direct evidence on achieved indoor conditions and household temperature preferences (Deller, Turner & Waddams Price, 2021).

Despite these limitations, perception-based indicators derived from EU-SILC remain widely used in European research, both as stand-alone measures and as components of multidimensional indices (Bollino & Botti, 2017; Carfora et al., 2022; Tovar Reaños et al., 2025). They provide harmonised information on experienced difficulty in securing adequate domestic energy services that expenditure measures may not capture. However, brief survey items offer only a partial representation of lived experience; qualitative research shows that energy

vulnerability also involves dwelling conditions, income stability, health, tenancy relations and social relations within and beyond the household (Middlemiss & Gillard, 2015). Comparative studies demonstrate limited overlap between perception- and expenditure-based classifications (Waddams Price et al., 2012; Deller et al., 2021). Waddams Price et al. (2012), for example, found that many low-income households spending more than 10% of their income on domestic energy did not report being unable to afford adequate warmth, while some households reporting such difficulty did not exceed the expenditure threshold. In Finland, Numminen et al. (2024) similarly found that households using oil heating within hybrid heating arrangements were more vulnerable under the 10% expenditure measure but did not report a corresponding energy-cost burden. Such divergence indicates that the measures capture different dimensions and household groups, reinforcing the case for using them complementarily rather than treating either as definitive.

Taken together, expenditure–income and perception-based indicators demonstrate that no single measure can provide a complete account of energy poverty. Expenditure-based indicators offer transparent, rule-based estimates of affordability pressure, but they may overlook hidden deprivation and remain sensitive to choices concerning thresholds, income, expenditure and equivalisation. Perception-based indicators capture experienced difficulty but may be influenced by expectations, adaptation, survey wording and national context, thereby constraining cross-country comparability. The literature therefore recommends using a basket of complementary indicators drawn from expenditure-based, consensual and direct-measurement approaches; composite indices may also be employed, provided that indicator selection, weighting and aggregation are transparent (Thomson, Bouzarovski & Snell, 2017; Castaño-Rosa et al., 2019; Teixeira et al., 2024). Measurement should also distinguish observed outcomes from the underlying drivers of energy vulnerability, including household income and needs, energy prices, dwelling performance, everyday practices and institutional conditions (Bouzarovski, 2014; Thomson, Bouzarovski & Snell, 2017). Because energy poverty varies across both space and time, household-level indicators can usefully be complemented by spatially disaggregated and longitudinal analyses that capture local vulnerability patterns, persistence and transitions into and out of energy poverty (Robinson, Lindley & Bouzarovski, 2019; Drescher & Janzen, 2021).

2.2 Modelling approaches to energy poverty

Early quantitative analyses of energy poverty generally began by operationalising household status through expenditure–income or perception-based indicators. In the UK fuel-poverty tradition, the original 10% rule classified households according to whether the expenditure required to obtain adequate domestic energy services exceeded 10% of household income (Boardman, 1991). Hills (2012) subsequently proposed the Low Income High Costs (LIHC) indicator for England, while 2M and M/2 were later recommended for EU-level comparative measurement (Rademaekers et al., 2016). These indicators constitute classification rules rather than econometric models. Empirical studies used cross-sectional regression methods to examine associations between energy poverty and household and dwelling characteristics. Healy and Clinch (2004), for example, modelled a four-category self-reported measure of households' ability to heat their homes adequately using ordered probit, whereas Fahmy, Gordon and Patsios (2011) estimated logistic models using the 2003 English House Condition Survey and applied the resulting coefficients to census and commercial data to produce small-area fuel-poverty estimates. These studies helped identify at-risk groups and supported the targeting of interventions. However, because their underlying household data were cross-sectional, they could not directly identify state dependence or transitions into and out of energy poverty, which require longitudinal models (Drescher & Janzen, 2021).

As multidimensional understandings of energy poverty developed, researchers increasingly combined expenditure-based, perception-based and housing-related indicators. Two related but methodologically distinct strategies should be distinguished. Composite indices combine selected indicators according to specified normalisation, weighting and aggregation rules, providing a broader measure than any individual indicator (Ntaintasis, Mirasgedis & Tourkolias, 2019; Thomson, Bouzarovski & Snell, 2017). Latent-variable models instead use relationships among observed indicators to estimate unobserved dimensions or household groups. Factor analysis represents common variation among indicators through continuous latent factors and can produce household-level factor scores. Taltavull de La Paz et al. (2022), for example, use EU-SILC data to identify dimensions of energy poverty associated with economic hardship and payment difficulties, poor housing quality, and dwelling size and location. Latent-

class analysis instead assumes a finite number of unobserved household groups and estimates the probability that each household belongs to them. Using four EU-SILC manifest variables, namely housing defects, inability to keep the home adequately warm, difficulty making ends meet and a heavy financial burden associated with housing costs (Bardazzi et al., 2023), distinguish energy-sufficient, energy-vulnerable and energy-poor households across five Mediterranean countries. These approaches move beyond a single binary threshold, but they generate different outputs, i.e. continuous factor scores or probabilistic class membership, and their results remain dependent on indicator selection and modelling assumptions.

Spatial analysis and GIS-based mapping have become increasingly important for examining the geography of energy poverty, but the approaches used in this literature are methodologically distinct. Small-area estimation applies relationships estimated from household surveys to spatially disaggregated census or administrative covariates. Fahmy, Gordon and Patsios (2011), for example, estimated logistic models using the English House Condition Survey and applied the resulting coefficients to census and commercial data to produce small-area fuel-poverty estimates. Indicator-mapping studies instead calculate energy-poverty measures directly from georeferenced microdata. Mulder et al. (2023) used household-level administrative data covering nearly 80% of Dutch households to compare the national and local distributions of affordability problems, dwelling energy quality and households' ability to participate in the energy transition.

Other studies use local multivariate and spatial-autocorrelation techniques to examine whether the composition and concentration of energy vulnerability vary across space. Robinson, Lindley and Bouzarovski (2019) and Zardo, Cortinovis and Lucertini (2024) compare global principal component analysis with geographically weighted principal component analysis, showing that the relative importance of vulnerability factors differs among neighbourhoods and municipalities. Lieth, Abel and Jünger (2025) construct a multidimensional energy-vulnerability index from 22 indicators for 16 EU countries and use local indicators of spatial association to identify spatial clusters of comparatively high and low vulnerability (Anselin, 1995). Spatial regression constitutes a further, distinct family of models that explicitly represents spatial dependence in outcomes, covariates or residuals (Anselin, 1988). Chen et al. (2022), for example, use spatially lagged variables and

a spatially autocorrelated error structure to analyse county-level energy burdens in the United States. Collectively, these approaches reveal spatial concentration and local heterogeneity that national averages may conceal. However, mapped clusters and spatial associations should not by themselves be interpreted as evidence of causal spillovers.

At the household level, longitudinal data make it possible to distinguish the prevalence of energy poverty at a particular point in time from its persistence and to differentiate transient from chronic deprivation. The methods used for this purpose are not interchangeable. Transition matrices and Markov processes describe movements between energy-poverty states over successive periods. Using longitudinal EU-SILC microdata for 26 European countries, Karpinska and Śmiech (2020), for example, examine transitions between energy poverty and subjective income poverty and show that income poverty substantially reduces the likelihood of escaping energy poverty. Mover–stayer models distinguish households that remain in a particular state from those that move between states; Chaton and Lacroix (2018) find that fuel poverty in France is generally transitory rather than an absorbing state, although a significant group remains persistently affected. Dynamic random-effects probit models instead estimate the relationship between previous and current energy-poverty status while accounting for observed characteristics and time-invariant unobserved household heterogeneity. Using seven waves of the German Socio-Economic Panel, Drescher and Janzen (2021) find genuine state dependence but also report that 78% of energy-poor households in their sample experience energy poverty only temporarily. Halkos and Kostakis (2023) similarly identify state dependence using four waves of Greek EU-SILC data and show that income, education, employment, migration background and dwelling characteristics are associated with persistence and transitions. These longitudinal approaches provide information that repeated cross-sectional prevalence estimates cannot reveal, although their conclusions remain sensitive to the energy-poverty indicator, observation period and definition of chronic deprivation.

A smaller but growing strand of the literature uses microsimulation to examine how energy-price shocks and policy reforms affect household energy affordability. These models apply specified counterfactual changes to representative household microdata while preserving heterogeneity in income, energy consumption, dwelling characteristics and location. Static models

generally hold household behaviour constant, whereas behavioural microsimulation incorporates estimated price or income responses. Chai, Ratnasiri and Wagner (2021), for example, simulate how increases in electricity prices alter the regional and income distribution of energy poverty in Queensland. In France, Berry (2019) models the household-level effects of carbon taxation and alternative cash-transfer designs, while Tovar Reaños and Lynch (2022) use a household demand system to simulate carbon taxes, compensatory measures and improvements in fuel efficiency. Bardazzi et al. (2024) assess how tariff interventions, social energy allowances and monetary transfers mitigated the effects of the 2021–2023 price shock on Italian households. Microsimulation can also evaluate structural interventions: Chaton (2025) examines how alternative renovation-grant designs affect renovation decisions and energy poverty in France. These models permit detailed comparison across income groups and household characteristics, but their results are model-based counterfactuals that depend on assumptions concerning price pass-through, behavioural responses, programme take-up, eligibility and targeting.

Agent-based modelling remains a promising but comparatively underdeveloped approach in energy-poverty research. Agent-based models represent households and other actors as heterogeneous agents whose decisions may depend on economic constraints, technologies, behavioural rules, social interactions and policy incentives; aggregate outcomes then emerge from repeated micro-level decisions (Rai & Henry, 2016). Most established household-energy applications focus on technology adoption or energy-efficiency transitions rather than directly modelling energy-poverty status (Hesselink & Chappin, 2019). Chersoni, DellaValle and Fontana (2022), for example, calibrate a behaviourally informed agent-based model of thermal-insulation investment using survey data for 19,538 EU homeowners and examine financial incentives, pro-environmental information and norm-based interventions. Pavlović, Ivezić and Živković (2022) use a survey-calibrated model to simulate household heating transitions in Serbia, showing how economic constraints, household attitudes, energy and technology prices and policy instruments shape the adoption of more efficient heating systems. A recent direct application is provided by Dejkam and Madlener (2025), who use household attributes from the English Housing Survey to model changes in fuel-poverty status under subsidy, grant and behavioural-nudge scenarios. Agent-based modelling offers considerable potential for analysing heterogeneous

adaptation, social influence, path dependence and interactions among policies, but direct and extensively validated applications to energy poverty remain limited.

Although still limited, a growing literature applies machine-learning methods, including random forests, gradient-boosted trees and neural networks, to classify households or areas by energy-poverty status and to identify complex, non-linear relationships among socioeconomic, housing and environmental predictors (Dalla Longa et al., 2021; Spandagos et al., 2023; Kalfountzou et al., 2025). These studies typically combine household-survey and socioeconomic data with dwelling and building characteristics; some applications additionally incorporate geospatial or remote-sensing information (Wang et al., 2021; Al Kez et al., 2024). Explainability tools, including variable-importance measures and SHAP values, can improve the transparency of model predictions and support the targeting of assistance schemes (Spandagos et al., 2023; Zheng & McKenna, 2025). However, most existing applications concern cross-sectional identification or classification rather than temporal forecasting, and their use as operational early-warning systems remains limited.

2.3 Forecasting energy poverty and key predictive variables

Forecasting energy poverty moves beyond retrospective measurement by estimating how energy-poverty indicators may evolve under projected economic and energy-market conditions. Existing empirical applications combine dynamic factor models with external projections of macroeconomic and energy-price variables to construct medium-term scenarios for EU Member States (Carfora, Scandurra & Thomas, 2022; Carfora & Scandurra, 2024). Broader predictive frameworks propose extending such analyses to socioeconomic and demographic change, technological developments, future energy demand and climate-related stressors, including rising temperatures and extreme events (Mochida, Chapman & McLellan, 2025). However, empirical models that jointly integrate all these domains remain limited; the literature is therefore more accurately characterised as a set of emerging and partially complementary forecasting approaches than as a mature, unified forecasting framework.

One of the few directly implemented EU-level forecasting approaches combines dynamic factor analysis, panel estimation and external macroeconomic

projections. Carfora et al. (2022) use latent factors summarising socioeconomic, living-condition and energy-related variables, together with projected macroeconomic scenarios, to forecast the EU-SILC share of the population unable to keep their home adequately warm across Member States up to 2025. Carfora and Scandurra (2024) extend this framework by incorporating projected changes in energy-commodity prices, particularly natural-gas prices, and examine how these alter the estimated return of energy-poverty levels to their pre-shock trajectories. These studies therefore provide evidence for dynamic-factor and panel-based forecasting under external scenarios; they do not substantiate the use of ARIMA or error-correction models, and they forecast a consensual indicator rather than the 2M or LIHC measures.

A second, less developed direction can be framed in terms of vulnerability and scenario-based forecasting. The established vulnerability-as-expected-poverty literature defines vulnerability *ex ante* as the probability that future household consumption or income will fall below a specified poverty threshold (Chaudhuri, Jalan & Suryahadi, 2002; Hoddinott & Quisumbing, 2010). By analogy, an energy-poverty application could estimate the probability that a household crosses an energy-poverty threshold under uncertain income, energy-price and climatic conditions. However, such a “vulnerability as expected energy poverty” approach has not yet become a standard empirical methodology. Existing forward-looking applications are narrower: Awaworyi Churchill et al. (2022), for example, combine estimated temperature effects from Australian household panel data with downscaled climate projections to predict the incidence of energy poverty over the remainder of the twenty-first century. More comprehensive scenarios jointly incorporating energy-price paths, climate change, carbon-pricing or subsidy reforms and alternative social-protection responses therefore remain primarily a research agenda rather than an established empirical strand.

A small but important strand of the literature incorporates energy poverty into model-based climate-policy scenario analysis by linking energy-system and macroeconomic projections with household-level data. Vandyck et al. (2023) combine a bottom-up energy-system model, the JRC-GEM-E3 computable general equilibrium model and a microsimulation based on the harmonised EU Household Budget Survey to estimate how strengthened EU climate action to 2030 affects household welfare and the incidence of energy poverty under alternative carbon-revenue recycling schemes. Their results show that carbon

pricing without compensatory measures can increase the number of energy-poor households, whereas transfers targeted at low-income households can reduce this risk. Fell, Pye and Hamilton (2020) propose a related approach for tracing the distributional effects of long-term UK low-carbon pathways across income groups, although their framework is primarily methodological and does not constitute an implemented energy-poverty forecast. These applications are therefore more accurately understood as conditional scenario projections than as statistical forecasts, and fully integrated models that jointly represent technological pathways, household investment constraints and energy-poverty dynamics remain uncommon.

Climate-informed forecasting of energy poverty remains relatively uncommon. One of the clearest direct applications is provided by Awaworyi Churchill, Smyth and Trinh (2022), who combine representative Australian household panel data with geographically localised weather observations and simulated future weather to project the incidence of energy poverty over the remainder of the twenty-first century. Contrary to the assumption that warming necessarily increases energy poverty, they find that additional cold days raise its incidence and that projected warming produces modest overall reductions in energy poverty in Australia, primarily because of declining exposure to cold temperatures. For Europe, Thomson et al. (2019) provide cross-sectional rather than forecasting evidence: their study of households in Gdańsk, Prague, Budapest and Skopje documents existing difficulties in maintaining adequate indoor cooling and identifies exposure, adaptive capacity and sensitivity as important dimensions of vulnerability to excessive heat. European climate–energy modelling nevertheless projects decreasing heating demand and increasing cooling demand under alternative climate scenarios up to 2050 (Larsen et al., 2020). However, these demand projections have not generally been translated into household-level forecasts of winter and summer energy poverty, leaving integrated European forecasting in this area underdeveloped.

Machine-learning methods are increasingly used to predict or classify contemporaneous energy-poverty status at household or subnational spatial scales. Existing applications employ gradient-boosted trees, random forests, decision trees and support-vector machines with household-survey, socioeconomic, dwelling and geospatial information (van Hove, Dalla Longa & van der Zwaan, 2022; Spandagos, Tovar Reaños & Lynch, 2023; Al Kez et al., 2024;

Balkissoon et al., 2024; Zheng & McKenna, 2025). These models can capture non-linear relationships and provide useful predictive classifications for identifying households or areas that may require assistance. However, most studies predict an observed energy-poverty category from cross-sectional data rather than forecast future household transitions over time. Evidence for forecasts at fine temporal resolution and operational early-warning systems therefore remains limited. Hybrid machine-learning and econometric approaches are promising, but their application requires longitudinal data, transparent validation and interpretable model outputs (González Garibay, Primc & Slabe-Erker, 2023).

Across forecasting, dynamic-panel, microsimulation and classification studies, several groups of predictive and explanatory variables recur. Their estimated importance is nevertheless context-, indicator- and model-specific, and an observed association should not automatically be interpreted as a causal effect or as evidence of out-of-sample forecasting ability:

- Energy prices and affordability – observed or projected electricity, gas and other household-energy prices, which affect energy expenditure and the probability of crossing an energy-poverty threshold (Chai, Ratnasiri & Wagner, 2021; Spandagos, Tovar Reaños & Lynch, 2023; Carfora & Scandurra, 2024).
- Household resources and labour-market status – household income, cash and social benefits, employment or unemployment and broader labour-force status, which determine households' capacity to absorb energy-price and income shocks (Drescher & Janzen, 2021; Spandagos, Tovar Reaños & Lynch, 2023; Tovar Reaños, Palencia-González & Labeaga, 2025).
- Housing and heating characteristics – dwelling condition and type, tenure, thermal insulation, energy efficiency and the principal heating system, which influence required energy consumption and the persistence of energy poverty (Healy & Clinch, 2004; Drescher & Janzen, 2021; Mulder et al., 2023).
- Social protection and institutional conditions – cash benefits, aggregate social-protection expenditure, the targeting of energy assistance, government effectiveness and regulatory quality (Certomà et al., 2023; Spandagos, Tovar Reaños & Lynch, 2023; Tovar Reaños, Palencia-González & Labeaga, 2025).



- Energy technologies and fuel mix – household heating sources, access to renewable-energy technologies and broader renewable-energy consumption and energy efficiency, all of which can influence exposure to energy costs and persistent deprivation (Drescher & Janzen, 2021; Zhao et al., 2022).
- Weather and climate conditions – geographically localised temperatures, cold and hot days, heatwaves and the associated need for heating or cooling (Thomson et al., 2019; Awaworyi Churchill, Smyth & Trinh, 2022).
- Demographic and health-related characteristics – household composition, age, disability or long-term illness, the presence of children and other circumstances that increase required indoor temperatures, occupancy or sensitivity to thermal discomfort (Healy & Clinch, 2004; Tovar Reaños, Palencia-González & Labeaga, 2025; Zardo, Cortinovis & Lucertini, 2024).

Although these domains provide a useful basis for model specification, only some variables, most notably projected macroeconomic conditions, energy prices and climatic variables, are routinely available in forward-looking form. Models intended for genuine forecasting must therefore distinguish between historically observed explanatory variables and variables for which credible future projections can be constructed.

3 TRANSPORT POVERTY

3.1 Concept and indicators

In this chapter, transport poverty is used as an umbrella term for situations in which individuals or households cannot afford private or public transport, lack adequate access to transport, or face mobility constraints that prevent them from reaching essential socioeconomic services and activities (Church et al., 2000; Lucas, 2012; Lucas et al., 2016; European Parliament & Council of the European Union, 2023b). The concept is therefore broader than low income or high transport expenditure alone: it arises from interactions between household resources and capabilities, the spatial distribution of opportunities, and the availability and accessibility of transport systems. In car-dependent settings, land-use patterns, infrastructure provision and institutional arrangements can make participation in everyday life contingent on access to a private vehicle, thereby creating structural disadvantage (Mattioli et al., 2020). Recent EU research accordingly treats transport-poverty vulnerability as multidimensional, encompassing affordability, accessibility and mobility (Primc et al., 2025), while Zabavnik et al. (2025) demonstrate that accessibility, relative prices and income dynamically shape public-transport use across the EU.

Although energy poverty and transport poverty are analytically distinct, they share several underlying drivers, including low income, rising energy prices, spatial disadvantage and limited access to efficient infrastructures and affordable alternatives. Energy poverty primarily concerns households' ability to secure socially and materially necessary domestic energy services, whereas transport poverty concerns their ability to attain necessary mobility and reach essential activities beyond the home; households exposed to both conditions experience what Simcock et al. (2021) describe as double energy vulnerability. Transport poverty therefore links residential location and transport provision with access to employment, education, healthcare, commercial services and social participation. When adequate mobility is unavailable or unaffordable, it can restrict access to these opportunities and reinforce existing poverty and social exclusion (Lucas, 2012). Vulnerability can be especially pronounced in car-dependent peripheral and suburban areas, where longer travel distances and inadequate alternatives to private vehicles increase exposure to transport-fuel price rises (Dodson & Sipe,



2008; Mattioli et al., 2020). Moreover, the risk is not confined to the lowest-income households: EU legislation recognises that low- and lower-middle-income households may also become vulnerable when they are significantly affected by road-transport price increases and lack the resources to shift to lower-emission vehicles or sustainable transport modes (Regulation (EU) 2023/955).

Indicators of transport poverty generally fall into four interrelated domains:

- Affordability indicators, capturing the financial burden of necessary transport relative to household income or other available resources;
- Accessibility indicators, measuring whether essential destinations and activities can be reached within reasonable time, cost and effort;
- Availability and quality indicators, reflecting the availability of suitable transport options, network coverage, frequency, reliability, timetable suitability and the safety and quality of travel conditions; and
- Individual-capability and physical-accessibility indicators, capturing whether people can convert formally available transport options into actual mobility, given disability, age, caring responsibilities, time constraints and the accessibility of vehicles, stops and infrastructure.

Although these four domains provide a useful organising framework, they are not exhaustive. Lucas et al. (2016) conceptualise transport poverty as an overarching condition encompassing transport affordability, mobility poverty, accessibility poverty and disproportionate exposure to transport-related externalities. Their working definition further identifies excessive travel time, particularly when it results in time poverty or social isolation, and dangerous, unsafe or unhealthy travel conditions as additional manifestations of transport poverty. Exposure to transport externalities includes disproportionate exposure to air and noise pollution, traffic-related injuries and deaths, as well as adverse effects of transport infrastructure, such as community severance and displacement. The boundaries between these domains are permeable: for example, an available service may remain effectively inaccessible if it is unreliable, physically unsuitable, unsafe to use or requires an unreasonable amount of travel time (Social Exclusion Unit, 2003; Lucas et al., 2016). With these overlaps in mind, the following discussion examines indicators within each of the four core domains, beginning with affordability.

Affordability indicators commonly relate household transport expenditure to income or total household expenditure. Although various context-specific benchmarks have been proposed, for example, thresholds based on the share of income devoted to commuting or public transport, no single expenditure threshold is universally accepted, and the appropriate benchmark depends on the prevailing transport, land-use and socioeconomic context (Serebrisky et al., 2009; Lucas, Mattioli, Verlinghieri & Guzman, 2016). Evidence reviewed in Australia and the United Kingdom links transport disadvantage and unaffordable mobility with difficulties in accessing employment, essential services and opportunities for social participation, thereby reinforcing social exclusion (Currie & Delbosc, 2011; Lucas, 2012; Lucas, Mattioli, Verlinghieri & Guzman, 2016). A central limitation of expenditure-share measures is that they capture observed spending rather than the resources required to satisfy essential mobility needs. Households facing severe budget constraints may walk, depend on lifts, reduce the number or distance of their journeys or forego trips altogether; low recorded expenditure may therefore indicate suppressed travel rather than adequate affordability (Mattioli, 2014; Serebrisky et al., 2009; Lucas, Mattioli, Verlinghieri & Guzman, 2016). This measurement problem parallels fuel-poverty research, where indicators based on required energy costs are used to avoid classifying households that under-consume energy because of financial constraints as non-fuel-poor (Hills, 2012). Expenditure-based affordability indicators should therefore be interpreted together with measures of unmet travel need, mobility and accessibility.

Accessibility indicators capture the extent to which land-use and transport systems enable individuals and population groups to reach spatially distributed opportunities and participate in everyday activities (Geurs & van Wee, 2004; Lucas, 2012; Pereira, Schwanen & Banister, 2017). Their operationalisation takes several forms. Location-based measures include cumulative-opportunity measures, which count destinations reachable within a specified travel-time threshold, and gravity-based measures, which weight opportunities according to the difficulty of reaching them. Person-based measures draw on time geography to incorporate individual space–time constraints, while utility-based or logsum measures derive accessibility from behavioural destination- and mode-choice models (Hansen, 1959; Hägerstrand, 1970; Geurs & van Wee, 2004; El-Geneidy & Levinson, 2006). Compared with expenditure-share measures, accessibility



indicators can reveal structural mismatches between residential locations, transport provision and essential destinations and disaggregate these disadvantages across places, transport modes and population groups (Lucas, van Wee & Maat, 2016; Pereira, Schwanen & Banister, 2017). Their results are nevertheless sensitive to the selection of opportunities, travel-time thresholds, transport modes, impedance functions, behavioural assumptions and data quality; different theoretically defensible implementations may therefore produce substantially different accessibility profiles and classifications of disadvantage (Geurs & van Wee, 2004; Páez, Scott & Morency, 2012).

Availability and quality indicators assess whether a usable public transport service is supplied, rather than merely whether a route or stop is geographically present. Relevant dimensions include spatial coverage and proximity to stops, service frequency and operating hours, reliability, total journey time, ease of interchange, comfort, perceived safety and the availability of understandable service information (Redman et al., 2013). This distinction is important because an area may be nominally served while still providing poor effective accessibility if services are infrequent, operate only during limited hours or require poorly coordinated connections. Schedule-based analyses demonstrate that public-transport accessibility can vary substantially between peak and off-peak periods, weekdays and weekends, revealing service gaps that static measures of route or stop availability may overlook (Fransen et al., 2015). Availability is also unevenly distributed: evidence from England identifies substantial spatial inequalities in service frequency and proximity and shows how these interact with income, car ownership and job accessibility to generate transport-poverty risks (Sun & Thakuriah, 2021). Ticketing and payment arrangements can create additional barriers; for example, cashless or smartphone-based systems may exclude users without bank accounts, payment cards, suitable devices or reliable internet access (Golub et al., 2022). Availability and quality indicators should therefore be evaluated across locations, times of day and population groups, particularly for people without access to a car and those whose work, care or other essential activities do not correspond to conventional peak-period service patterns (Hine & Grieco, 2003).

Capability and physical-accessibility indicators capture personal, household and social constraints, including disability, age, caregiving responsibilities, fear of crime and gendered or cultural norms, that influence whether people can actually

use the transport options nominally available to them (Sen, 1999; Lucas, 2012). This perspective recognises that mobility is not determined only by physical infrastructure and financial cost; effective use also depends on how personal circumstances and wider social, spatial and cultural contexts shape people's ability to convert transport resources into access to valued activities (Pereira, Schwanen & Banister, 2017). Studies of older adults, people with mobility disabilities and travellers with caregiving responsibilities identify barriers including inaccessible vehicles and pedestrian environments, distance to stops, missing ramps or step-free connections, limited places to rest and the practical difficulties of travelling with children or other dependants (Rosenberg et al., 2013; Nordbakke, 2013). Fear of crime and sexual harassment can also alter route, mode and time-of-day choices, especially among women and other travellers who perceive themselves to be particularly vulnerable, even where services are nominally available (Loukaitou-Sideris, 2014; Ceccato & Loukaitou-Sideris, 2020). Because such constraints are heterogeneous and context-dependent, they are not always adequately represented in conventional transport indicators and models. Nevertheless, they are essential for explaining why a formally accessible transport system may remain effectively inaccessible to vulnerable groups and for understanding lived experiences of mobility deprivation (Church, Frost & Sullivan, 2000; Lucas, 2012).

3.2 Modelling approaches to transport poverty

Early analyses relevant to what is now conceptualised as transport poverty drew heavily on spatial mismatch theory, which links adverse labour-market outcomes to the geographical separation between workers' residences and suitable employment opportunities, particularly among low-skilled racial and ethnic minority populations living in segregated US inner-city neighbourhoods (Kain, 1968; Preston & McLafferty, 1999; Gobillon, Selod & Zenou, 2007). Empirical studies of US metropolitan areas generally show that access to suitable jobs—especially by public transport—can affect employment, working hours, commuting patterns and earnings, although these effects vary across places and population groups. In San Francisco and Los Angeles, greater transit-based job accessibility was associated with higher probabilities of employment and of working at least 30 hours per week among low-skilled workers without cars, while accessibility and commuting outcomes differed markedly between car and



public-transport users in the San Francisco Bay Area (Kawabata, 2003; Kawabata & Shen, 2007). In Los Angeles, proximity to low-wage jobs increased the likelihood that welfare recipients obtained employment in their neighbourhoods and was associated with shorter commutes and higher earnings. Similarly, the expansion of the rapid-transit system in the San Francisco Bay Area increased the hiring of Latino workers by firms located near new stations, although little corresponding effect was found for Black workers (Ong & Blumenberg, 1998; Holzer, Quigley & Raphael, 2003).

Contemporary approaches adopt more sophisticated activity-based models, which simulate individuals' daily schedules and travel behaviour, allowing researchers to capture trip chaining and temporal constraints associated with daily activities (Kitamura, 1988; Bowman & Ben-Akiva, 2001; Shiftan & Ben-Akiva, 2011). By modelling whole daily activity patterns rather than isolated trips, these frameworks can incorporate individual and household heterogeneity; empirical analysis shows that sociodemographic factors and residential context influence daily travel time (Schwanen, Dijst & Dieleman, 2002). This activity-based perspective thus complements spatial mismatch approaches by highlighting not only where opportunities are located, but also when and under what temporal and social constraints they can be reached.

GIS-based accessibility analyses, sometimes combined with spatial statistical or econometric methods, are widely used to identify spatial patterns of transport disadvantage and assess how infrastructure changes affect accessibility outcomes (Anselin, 1988; Páez, Scott & Morency, 2012; Delmelle & Casas, 2012). By combining spatially explicit accessibility indicators with socioeconomic data, these analyses can identify areas of poor access that coincide with concentrations of low-income households or other vulnerable groups and assess how new lines, stations or service changes redistribute accessibility benefits and burdens (Delmelle & Casas, 2012; Titheridge et al., 2014).

Network analysis techniques are used to examine connectivity, path structure, node importance and network accessibility, providing insights into how transport-network topology shapes accessibility and travel performance (Levinson, 2012; Curtis & Scheurer, 2010; Cats, 2017). Such analyses can identify locations that are poorly integrated into public transport networks and have weaker access to opportunities, while individual-level accessibility studies show

that these disadvantages may be particularly pronounced for people with disabilities and other mobility-constrained groups (Curtis & Scheurer, 2010; Casas, 2007).

Spatial accessibility and transport-poverty assessments increasingly integrate socio-demographic characteristics, such as income, ethnicity, age, disability and car ownership, to capture how spatial structures interact with social inequalities and to identify groups for whom a given level of physical connectivity may still translate into inadequate access (Guagliardo, 2004; Lucas, 2012; Titheridge et al., 2014). In doing so, spatial and network-based approaches move beyond purely technical assessments of transport performance and provide a more socially differentiated understanding of how infrastructure and planning decisions shape patterns of transport poverty.

Microsimulation and agent-based models are used to represent heterogeneous households and their adaptive behaviours within integrated land-use and transport systems (Miller & Salvini, 2001; Arentze & Timmermans, 2004; Moeckel, 2017). By modelling individual agents with distinct socio-demographic attributes, preferences and constraints, these approaches can capture distributional and feedback effects of policy interventions. Activity-scheduling microsimulation, for example, represents the generation, timing and sequencing of household activities and trips (Roorda et al., 2008), while land-use microsimulation can model how transport costs and travel-time constraints influence household relocation choices (Moeckel, 2017). Telecommuting studies likewise show that changes in working arrangements can alter the spatial and temporal pattern of household travel and reduce peak-period travel (Pendyala, Goulias & Kitamura, 1991).

Machine-learning approaches, including random forests, gradient boosting and neural networks, are increasingly applied to mobility and traffic datasets to identify travel modes, model mode choice and predict traffic conditions, including non-linear relationships that may be difficult to represent with conventional models (Lu et al., 2019; Ma et al., 2015; Wang & Ross, 2018). Such models can incorporate trip characteristics, socio-demographic attributes and built-environment variables; Wang and Ross (2018), for example, found that extreme gradient boosting predicted mode choice more accurately than a multinomial logit model in their application. Although machine-learning models are often criticised for limited transparency, feature-importance and related interpretability



tools can help clarify which variables drive their predictions. Their application to identifying transport-poverty hotspots or providing early warnings nevertheless remains a potential extension rather than an outcome demonstrated by the studies cited here.

3.3 Forecasting transport poverty and key predictive variables

Forecasting transport poverty involves modelling how risks of inadequate or unaffordable mobility and accessibility may evolve under changing economic, technological, spatial and environmental conditions, rather than treating current patterns of deprivation as fixed. Scenario based analyses of transport and land use can be used to examine how changes in transport costs, service provision, infrastructure, land use and travel behaviour affect accessibility across different places and population groups (Geurs & van Wee, 2004; Banister, 2008). This literature also highlights that transport policies and service changes can distribute benefits and burdens unevenly and may deepen mobility and accessibility disadvantages for already vulnerable groups if distributional effects are not explicitly considered, emphasising the need to integrate equity-sensitive assessment into transport and land-use planning (Martens, 2017; Lucas et al., 2016; Uteng & Lucas, 2017).

Key predictive and explanatory variables in transport-poverty forecasting models include:

- Household resources and vulnerability characteristics, including disposable income, employment status, material deprivation, household composition, age, disability, caring responsibilities and car availability, which influence both households' capacity to absorb transport costs and their ability to convert formally available transport options into effective mobility (Lucas, 2012; Titheridge et al., 2014; Sun & Thakuriah, 2021; Cludius et al., 2024);
- Transport prices and related policies, including fuel and electricity prices, public-transport fares, fare concessions and subsidies, parking charges and road tolls, which determine the affordability of private and public transport and may create particular pressures for low-income households dependent on car travel (Goodwin et al., 2004; Lucas et al., 2016; Mattioli et al., 2020; Cludius et al., 2024);

- Public-transport supply and performance, including network coverage, proximity to stops, service frequency, operating hours, timetable suitability and reliability, which determine whether nominally available services constitute usable mobility options at the places and times when they are needed (Social Exclusion Unit, 2003; Fransen et al., 2015; Sun & Thakuriah, 2021);
- Land-use and destination changes, including suburban expansion, densification and the relocation of employment, healthcare, education, childcare, retail and other essential services, which reshape travel distances and the number of opportunities reachable within reasonable time, cost and effort (Cervero & Kockelman, 1997; Geurs & van Wee, 2004; Ewing & Cervero, 2010; Titheridge et al., 2014);
- Changes in employment locations, working-time arrangements and everyday activity schedules, which can alter the timing and regularity of travel needs and create temporal mismatches between required journeys and public-transport provision, particularly outside conventional peak periods (Hine & Grieco, 2003; Schwanen et al., 2008; Kalleberg, 2011; Fransen et al., 2015);
- Vehicle access and changes in mobility technologies, including patterns of car ownership and car dependence, the diffusion of electric vehicles and shared-mobility services, and access to charging infrastructure, which may alter both the availability of mobility alternatives and households' exposure to transport costs (Sprei, 2018; Mattioli et al., 2020; Cludius et al., 2024);
- Digitalisation of transport services, including digital ticketing, cashless payment and mobility-as-a-service platforms, which may expand and integrate mobility options but may also exclude users without suitable devices, internet access, bank accounts, payment cards or sufficient digital skills (Kamargianni et al., 2016; Pangbourne et al., 2020; Golub et al., 2022);
- Climate and weather-related hazards, including extreme heat, heavy precipitation, flooding and snow, which can damage infrastructure, reduce network reliability and increase journey times, with potentially greater consequences for people and places with limited modal alternatives or network redundancy (Koetse & Rietveld, 2009; Lucas et al., 2016; Pregnotato et al., 2017); and



- Infrastructure investment, maintenance and network restructuring, which shape the spatial coverage, capacity, quality and long-term reliability of transport networks and interact with land-use development to redistribute accessibility across central, peripheral and disadvantaged areas (Banister, 2008; Bertolini, 2012; Titheridge et al., 2014; Sun & Thakuriah, 2021).

Scenario-based forecasting approaches can be used to explore how interacting pressures, such as fuel-price increases, climate-related infrastructure disruption and constraints on public transport funding, may raise future transport-poverty risks. Integrated land-use-transport models and accessibility measures enable analysts to assess how changes in transport costs, service provision and the spatial distribution of employment alter access to opportunities across different places and population groups (Geurs & van Wee, 2004; Banister, 2008). When combined with evidence on transport disadvantage, these approaches suggest that adverse changes may be especially consequential for low-income and transport-dependent households with fewer mobility alternatives (Lucas et al., 2016; Martens, 2017). Research on climate and transport further shows that flooding and other adverse weather conditions can damage infrastructure, reduce speeds and reliability, and disrupt network accessibility (Koetse & Rietveld, 2009; Pregolato et al., 2017). Such disruptions may exacerbate existing transport disadvantage where networks have limited redundancy or affected households lack alternative modes (Lucas et al., 2016).

These approaches are particularly valuable for identifying areas in which socio-economic disadvantage, poor accessibility and limited transport alternatives overlap, by combining spatially disaggregated accessibility indicators with socio-demographic and transport-network data (Titheridge et al., 2014; Lucas et al., 2016). The resulting evidence underscores the importance of incorporating explicit equity objectives into long-term transport planning and targeted investment. Without such measures, changes in transport provision and wider policy transitions may reproduce or deepen transport poverty among already marginalised groups (Martens, 2017; Uteng & Lucas, 2017).

4 HOUSING POVERTY

4.1 Concept and indicators

Housing poverty refers to a condition in which households are unable to access housing that is affordable, secure, of adequate quality and appropriate to their needs (UN-Habitat, 2003; Stone, 2006; Haffner & Boumeester, 2010). Like transport poverty, this dimension is strongly connected to energy poverty, as poor thermal efficiency, including insufficient insulation, increases the energy required to maintain adequate indoor temperatures (Boardman, 2010). Housing poverty reflects both financial stress and physical inadequacy and is increasingly recognised as an important dimension of multidimensional deprivation in both high- and low-income contexts. Poor housing conditions are associated with adverse physical and mental health outcomes and broader socioeconomic disadvantage (Thomson et al., 2013; Baker et al., 2016; Tunstall et al., 2013). Housing poverty is not limited to homelessness; it also encompasses overcrowding, insecure tenure, excessive housing cost burdens, poor structural quality and exposure to environmental hazards. Empirical studies show that high housing cost burdens and arrears are associated with material deprivation and social exclusion (Tunstall et al., 2013; Norris & Winston, 2012), while overcrowding and substandard dwellings are linked to respiratory illness and mental distress and, among children, poorer educational performance (Evans, 2003; Baker et al., 2016; Solari & Mare, 2012). Moreover, low-income households are disproportionately likely to live in hazard-prone or polluted areas, exposing residents to heightened environmental risks and reinforcing spatially concentrated disadvantage (Walker, 2012).

Indicators of housing poverty are typically grouped into four main domains:

- Affordability indicators, such as housing cost overburden rates;
- Adequacy and quality indicators, including structural defects, dampness and thermal comfort;
- Security indicators, capturing tenure stability and eviction risk; and
- Suitability indicators, such as overcrowding and space standards.

Affordability is commonly measured using housing-cost-to-income ratios, although the precise threshold and income definition vary. In much North



American policy and research, households spending more than 30% of their gross income on housing are classified as housing-cost burdened, while Eurostat defines housing-cost overburden as total housing costs exceeding 40% of disposable income (Hulchanski, 1995; Bogdon & Can, 1997; Stone, 2006; Eurostat, 2024). This ratio-based approach has been widely adopted in policy and research because it is simple to compute and facilitates comparisons across groups and countries. High housing-cost burdens are associated with arrears and material deprivation and may also contribute to constrained housing choices, including overcrowding (Tunstall et al., 2013; Norris & Winston, 2012). However, this approach has limitations similar to energy- and transport-poverty measures: it does not adequately account for variations in necessary non-housing expenditure, such as childcare, healthcare and transport, or for differences in household composition, housing quality and local housing-market conditions. It may also be difficult to interpret in informal or non-market housing arrangements and can misclassify higher-income households that voluntarily spend a large share of their income on housing as experiencing affordability problems (Hancock, 1993; Hulchanski, 1995; Stone, 2006; Haffner & Boumeester, 2010; Bramley, 2012).

Residual-income approaches assess whether households have sufficient income remaining after housing costs to meet other basic needs at a socially acceptable standard. They offer a more nuanced perspective than fixed cost-to-income ratios because they explicitly account for differences in necessary expenditure by household type and, by context where appropriate budget standards are available (Stone, 2006; Stone et al., 2011). Empirical applications show that residual-income and ratio measures can identify different patterns of housing vulnerability, with residual-income measures being particularly informative for low-income households and families with greater non-housing expenditure needs (Kutty, 2005; Stone et al., 2011; Haffner & Heylen, 2011). Evidence also suggests that affordability measures are more informative when assessed alongside payment difficulties and material hardship rather than treated as stand-alone thresholds (Bramley, 2012). However, residual-income measures require detailed information on household budgets and the specification of normative minimum-income or expenditure standards, making them more data-intensive and helping to explain why they are used less routinely than simple ratio measures.

Quality indicators are often derived from housing surveys and administrative data, capturing conditions such as leaks, mould, inadequate insulation and unsafe wiring. These indicators are closely aligned with lived experiences of housing deprivation and are associated with respiratory illness, psychological distress, domestic accidents and excess winter mortality (Evans, 2003; Thomson et al., 2013; WHO, 2018). For example, evidence from New Zealand and broader international reviews indicates that damp and cold homes are associated with respiratory symptoms, cardiovascular problems and mental health difficulties, with children, older adults and people with pre-existing health conditions being particularly vulnerable (Howden-Chapman et al., 2007; Liddell & Guiney, 2015; WHO, 2018). However, definitions, thresholds and survey instruments vary across national reporting systems, complicating cross-country comparisons and the construction of harmonised housing-quality indices (OECD, 2025).

Overcrowding measures, based on persons per room or bedroom and minimum space or occupancy standards, are commonly used to assess housing suitability and have been associated with reduced privacy, family conflict and poorer child well-being, while evidence also links overcrowded housing to lower educational attainment (Evans et al., 1998; Goux & Maurin, 2005). Yet, objective density measures do not necessarily capture residents' perceived crowding or whether the available space is appropriate for the composition and needs of a particular household. Their interpretation may also depend on cultural norms and living practices, potentially misclassifying some multigenerational households or households with different expectations regarding shared space (WHO, 2018; Torshizian & Grimes, 2021). As a result, while quality and overcrowding indicators provide valuable insight into material housing deprivation, they must be interpreted in context and, where possible, complemented by qualitative or perception-based measures to capture how residents themselves experience housing adequacy and crowding.

4.2 Modelling and forecasting housing poverty

Housing poverty models and analytical frameworks increasingly integrate housing-market dynamics, welfare regimes and urban spatial structures, recognising that affordability and housing exclusion emerge from the interaction of household resources, price formation, regulation and spatial opportunity

structures rather than from household income alone (Fitzpatrick & Stephens, 2014; Norris & Winston, 2012). Hedonic pricing models are widely used to estimate how structural, neighbourhood and locational attributes are capitalised into house prices and rents (Rosen, 1974; Malpezzi, 2003). When combined with broader urban economic, spatial or policy-simulation models, these estimates can help assess how market and regulatory changes affect affordability across locations and household groups. Related theoretical and empirical studies show that restrictive planning regimes and inelastic housing supply can amplify the effect of demand shocks on house prices, thereby intensifying affordability pressures and limiting lower-income households' access to high-demand locations (Gyourko et al., 2013; Glaeser & Gyourko, 2018; Hilber & Vermeulen, 2016).

Microsimulation models allow researchers to estimate how tax and benefit reforms affect household disposable incomes, poverty and, where housing costs and benefits are represented, housing cost burdens by applying alternative policy rules to large, representative household datasets (Bourguignon & Spadaro, 2006; Figari et al., 2015). European applications show that housing allowances and mortgage interest tax relief can have substantial and distributionally differentiated effects: housing allowances can reduce poverty among recipient groups, whereas mortgage interest tax relief often benefits higher-income owner-occupiers disproportionately (Figari et al., 2016). Because static microsimulation models generally hold rents, housing supply and household behaviour constant, potential market responses must be considered separately. Quasi-experimental evidence from France shows that housing benefits may be partly capitalised into higher rents, weakening their intended redistributive effect (Fack, 2006). Together, hedonic, housing-market and microsimulation approaches indicate that housing poverty is strongly affected by policy design and market regulation, reinforcing the need to evaluate affordability through institutional and spatial contexts as well as household characteristics.

Forecasting housing poverty requires linking projections of housing-market outcomes, such as house prices, rents, mortgage costs and new housing supply, to household income and tenure data, allowing future housing cost burdens or residual incomes to be estimated. Housing market trajectories can be generated using error-correction house-price equations, rent models or integrated spatial and macroeconomic frameworks (Meen, 2001; Malpezzi, 1999; Andrews et al.,

2011). Key predictive variables include household incomes and wage growth, credit conditions, including mortgage interest rates, loan-to-value and loan-to-income limits and credit availability, construction costs, population growth and household formation, migration flows and planning regulations. Collectively, these variables determine housing demand, financing conditions and the responsiveness of new supply (Meen, 2001; Andrews et al., 2011; Glaeser & Gyourko, 2018). Empirical studies show that restrictive land-use regulation and sluggish supply responses cause demand shocks to be absorbed more strongly through house price increases than through new construction, while separate evidence shows that expansions in mortgage credit can also raise house prices (Hilber & Vermeulen, 2016; Caldera Sánchez & Johansson, 2013; Favara & Imbs, 2015). In high-demand locations with inelastic supply, these processes can intensify affordability pressures and limit lower-income households' access to housing (Gyourko et al., 2013).

Recent housing research increasingly considers climate hazards as flooding and extreme heat can reshape housing adequacy, safety and affordability. Evidence shows that homes exposed to the rise of the sea level may sell at discounts relative to otherwise comparable properties, while research on summer energy poverty demonstrates that an inability to afford adequate cooling creates an additional form of housing vulnerability during periods of extreme heat (Bernstein et al., 2019; Thomson et al., 2019). Climate risks and adaptation measures can also have unequal distributional consequences: low-income households generally have fewer resources to protect or retrofit their dwellings or to relocate, while resilience investments may increase local property values and contribute to displacement or climate gentrification if equity is not incorporated into their design (Shi et al., 2016; Anguelovski et al., 2019). Forward-looking assessments of housing poverty should therefore combine household income, tenure and housing-cost information with projected hazard exposure, expected damage, cooling needs and adaptation capacity. Emerging applications that combine the rise of the sea level projections with the location of affordable housing demonstrate how such integrated approaches can identify future concentrations of climate-related housing vulnerability (Buchanan et al., 2020).



5 WATER POVERTY

5.1 Concept and indicators

Water poverty refers to the inability to access sufficient, safe, reliable and affordable water for basic domestic needs (Sullivan, 2002). It takes into account both physical scarcity (Falkenmark et al., 1989) and socio-economic barriers to access, including infrastructure failures, price barriers and institutional exclusion (Lawrence, Meigh & Sullivan, 2002). The Water Poverty Index (WPI thereafter), for example, explicitly combines resource availability, access, capacity, use and environment, and empirical applications show that deficits in socio-economic capacity and access can be as important as biophysical scarcity in characterizing water-related deprivation (Sullivan, 2002; Manandhar, Pandey & Kazama, 2012).

While traditionally associated with low-income and arid regions, water poverty is increasingly relevant in high-income countries due to infrastructure ageing, long-term underinvestment, droughts and rising tariff pressures. Studies from the UK, US and Southern Europe document affordability problems and unequal exposure to unreliable services among low-income and marginalised communities, even where aggregate coverage rates are high; in parts of the US, non-payment has also led to large-scale water shut-offs (Jepson, 2014). This emerging literature highlights that water poverty is not only a question of hydrological scarcity, but also of governance, pricing regimes and regulatory frameworks, with marketisation and cost-recovery policies sometimes exacerbating exclusion for already vulnerable households (Bakker, 2010).

Indicators are often structured around the WPI, which integrates dimensions of resource availability, access, capacity, use and environmental integrity into a single composite measure (Sullivan, 2002; Lawrence, Meigh & Sullivan, 2002). The WPI framework was developed to move beyond purely volumetric or infrastructural metrics and to capture how social, economic and environmental factors jointly shape water-related deprivation. Empirical applications in South Africa, Tanzania and Nepal show that WPI scores reflect different combinations of constraints across these dimensions, rather than physical scarcity alone, underscoring the need for location- and scale-specific interventions involving water access, socio-economic capacity and environmental management



(Manandhar et al., 2012). Komnenic et al. (2009), however, caution that composite WPI scores can obscure the underlying drivers and recommend examining the individual indicators alongside the aggregate index.

At the household level, indicators typically include hours of water availability, distance or time to water sources, affordability of water bills and water quality or acceptability (Gleick, 1996; Howard & Bartram, 2003; Jepson, 2014). Studies show that long collection times and intermittent supply are associated with reduced water consumption, compromised hygiene practices and gendered time burdens, particularly for women and children (Howard & Bartram, 2003; Cairncross & Feachem, 1993; Crow & Sultana, 2002). Likewise, high tariffs relative to income can force households to under-consume or rely on alternative sources (Jepson, 2014), while poor water quality is linked to elevated rates of diarrhoeal disease and other health problems (Howard & Bartram, 2003; Wolf et al., 2018). Together, these indicators highlight that water poverty is multidimensional, capturing not only water availability, but also how reliably, at what cost, with what effort and with what health risks it can be obtained.

5.2 Modelling and forecasting water poverty

Hydro-economic models combine hydrological systems with socio-economic demand modules to simulate water scarcity, allocation and affordability under changing climatic and demographic conditions (Harou et al., 2009; Ward & Pulido-Velázquez, 2008; Medellín-Azuara et al., 2008). Typically formulated as basin-scale optimisation or simulation frameworks, they represent river flows, reservoir operations and groundwater dynamics alongside sectoral water demands (households, agriculture, industry) and economic values, allowing analysts to explore trade-offs between competing uses and to identify cost-effective adaptation and pricing strategies. Empirical applications show that such models can reveal how climate-induced reductions in runoff or storage disproportionately affect low-income users when allocation and tariff regimes prioritise high-value agricultural or industrial uses, thereby highlighting potential distributional and poverty implications of water management decisions (Ward & Pulido-Velázquez, 2008; Brouwer & Hofkes, 2008; Medellín-Azuara et al., 2008).

Forecasting models building on these frameworks integrate precipitation and temperature projections, reservoir storage levels, groundwater depletion trends,

tariff structures and household income trajectories to estimate future water poverty risks (Vörösmarty et al., 2000; Arnell, 2004; Hanasaki et al., 2013). Studies using combined climate–hydrology–economy scenarios suggest that, without targeted affordability policies and sufficient investment in infrastructure, climate change and population growth are likely to increase both the incidence and depth of water-related deprivation, even in regions that remain water-abundant in aggregate terms (Gosling & Arnell, 2016; Jepson & Brown, 2014; Heyman et al., 2022). Such results suggest that future water poverty is shaped not only by changing hydrological regimes, but also by evolving income distributions, tariff designs and governance arrangements that mediate households’ ability to pay for safe and reliable water services.

Key predictive variables include rainfall variability and drought frequency, which directly affect surface and groundwater availability and have been linked to heightened water stress and livelihood insecurity, particularly for already poor households (Vörösmarty et al., 2000; Arnell, 2004; Dercon, 2004; Gosling & Arnell, 2016); infrastructure leakage rates, which reduce effective supply, increase system costs and can undermine the reliability of service in low-income areas (Kingdom et al., 2006; Loucks & van Beek, 2017); urban population growth, which concentrates demand and often outpaces extension and upgrading of water networks, thereby intensifying service rationing and informal access in rapidly growing cities (McDonald et al., 2011; UN DESA, 2018); water governance effectiveness, including regulatory quality, tariff-setting, pro-poor policies and corruption control, which shapes both investment levels and the extent to which utilities prioritise universal service versus commercial logics (Bakker, 2010; Pahl-Wostl, 2009; OECD, 2015); and household-level poverty and consumption behaviour, as income constraints, price sensitivity and coping strategies (e.g. under-consumption, reliance on unsafe sources, informal vendors) determine how macro-level scarcity and pricing decisions translate into concrete experiences of water deprivation (Whittington et al., 1990; Nauges & Whittington, 2010; Jepson, 2014).

6 FOOD POVERTY

6.1 Concept and indicators

Food poverty refers to the inability to secure nutritionally adequate, culturally appropriate and socially acceptable food on a reliable basis (FAO, 2008; Dowler & O'Connor, 2012). It is distinct from hunger alone, encompassing both the quantity and quality of food access, as well as the stability and dignity with which food is obtained (Radimer et al., 1990; Anderson, 1990).

Indicators of food poverty include food insecurity experience scales, such as the Food Insecurity Experience Scale (FIES thereafter), as well as proxy measures such as reliance on food banks, skipped meals, dietary diversity scores and the affordability of healthy diet baskets (Ballard et al., 2013; Herforth et al., 2020; Kennedy et al., 2011; Loopstra & Tarasuk, 2015).

6.2 Modelling and forecasting food poverty

Empirical research shows that food poverty is strongly shaped by income constraints and volatile food prices, with low-income households disproportionately exposed to rising costs and more likely to adopt coping strategies such as reducing meal size, lowering dietary diversity or prioritising cheaper, energy-dense but nutrient-poor foods (Loopstra & Tarasuk, 2013; Headey & Martin, 2016; Barrett, 2010). It is also mediated by geographic access and transport poverty. For example, limited availability of affordable healthy food in areas with poor retail provision and by transport constraints that make it difficult to reach better-stocked outlets (Cummins & Macintyre, 2006; Walker, Keane & Burke, 2010). In addition, social support systems, including formal safety nets (cash transfers, food assistance, school meals) and informal networks of family, friends and community organisations, play a critical buffering role. Where such supports are weak or fragmented, economic shocks and individual life events translate more readily into food insecurity and material deprivation (Dowler & O'Connor, 2012; Loopstra et al., 2016; Gentilini, 2013).

Forecasting models of future food poverty and food insecurity commonly link crop-yield projections with global price and household-welfare modules, while broader vulnerability assessments may additionally incorporate local food-retail

access, household incomes and social-protection coverage (Schmidhuber & Tubiello, 2007; Hertel et al., 2010; Headey & Martin, 2016). Climate–crop models linked with economic models show that projected changes in temperature and precipitation can significantly reduce yields in many regions, driving up food prices and disproportionately harming poor, net food-purchasing households unless counterbalanced by productivity gains or safety nets (Lobell et al., 2008; Hertel, Burke & Lobell, 2010; Nelson et al., 2009). Incorporating indicators of local food retail access and household incomes helps capture how macro-level shocks translate into micro-level constraints on diet quantity and quality, while measures of social protection coverage (cash transfers, food subsidies, school feeding) are critical for assessing governments’ capacity to buffer vulnerable groups from these shocks (Gentilini, 2013; Alderman, 2016).

Variables such as extreme weather events, fertiliser and energy costs, biofuel policies and geopolitical instability are relevant inputs in predictive modelling. Evidence from global food-price spikes and regional crises shows that adverse weather in important production areas, increases in fertiliser and energy prices, and policy-driven demand for biofuels can each contribute to higher food prices and volatility, although their relative importance varies across crises and commodities, with marked implications for food insecurity among the poor (Headey & Fan, 2008; Timmer, 2010). Trade restrictions, especially export bans, can amplify international price spikes and transfer volatility to import-dependent countries (Martin & Anderson, 2012; Timmer, 2010). Conflict-related disruptions can likewise interrupt agricultural production and international trade, supporting the incorporation of geopolitical and trade variables into food-poverty forecasting models (Jagtap et al., 2022). To summarise, the literature suggests that forecasts of food poverty should link biophysical yield projections with market dynamics, policy regimes and the evolving capacity of social protection systems to shield vulnerable households from systemic shocks.

7 DIGITAL POVERTY

7.1 Concept and indicators

The increasing importance of digital technologies has introduced another dimension of poverty, often termed digital poverty. It refers to the inability to access, afford and effectively use digital technologies that are increasingly important for education, employment, healthcare and civic participation (Barrantes Cáceres, 2007; van Dijk, 2006; Helsper, 2012; Warschauer, 2003). It is not reducible to a simple lack of internet connectivity or digital devices. Rather, it is multidimensional, encompassing access to appropriate devices, reliable and affordable connectivity, digital skills and literacies, and forms of use that allow individuals to obtain tangible social and economic benefits (van Dijk, 2006; Selwyn, 2004; Helsper, 2012; Ragnedda & Muschert, 2013).

Empirical studies show that inequalities in device type and quality (e.g. smartphone-only versus computer access), the affordability and reliability of connectivity, and the ability to maintain access shape what users can actually do online, potentially reinforcing existing socio-economic inequalities (Tsetsi & Rains, 2017). Likewise, gaps in digital skills and confidence mean that, even where infrastructure is available, users with lower incomes or educational attainment may engage in a narrower range of online activities and be less likely to undertake informational, educational, career-related or commercial activities. These usage inequalities constrain the potential of digitalisation to reduce poverty and social exclusion (Hargittai, 2010; Helsper, 2012; van Deursen & van Dijk, 2014).

Indicators include broadband access rates, device ownership, data affordability, digital literacy levels and frequency of online engagement with essential services, each capturing a different layer of digital deprivation. Broadband and high-speed access rates are commonly used to map infrastructural gaps and rural–urban divides, while higher broadband adoption in rural areas has been associated with income growth and lower unemployment growth (Whitacre et al., 2014). Device ownership, as well as the type and quality of devices available, also matters because reliance solely on smartphones can restrict the range and complexity of online activities, thereby reproducing usage inequalities despite nominal connectivity (Pearce & Rice, 2013; Tsetsi & Rains, 2017).



Data-affordability indicators, such as the share of income required for connectivity or the price of a standard data basket, capture important cost barriers to digital inclusion (International Telecommunication Union, 2022). Survey evidence indicates that these barriers are particularly pronounced among lower-income groups and can lead to non-adoption, interrupted access or constrained connectivity (Galperin, 2017; Gonzales, 2016). Digital literacy levels, measured through self-assessed skills or performance-based tests, are associated with more diverse forms of internet use and a greater ability to undertake informational, educational, career-related and commercial activities (van Deursen & van Dijk, 2014; Hargittai, 2010). Finally, indicators capturing the frequency of online engagement with essential services, such as applying for benefits, accessing e-health, using online banking or engaging with educational platforms, provide insight into meaningful use and its outcomes. Research indicates that socio-economic and demographic inequalities in these uses and outcomes persist even where basic internet access is available (Helsper, 2012; Scheerder et al., 2017).

7.2 Modelling and forecasting digital poverty

Digital-poverty modelling draws on the broader literature on digital divides, digital exclusion and broadband adoption to estimate the risk or intensity of inadequate digital access and use. Rather than measuring only differences between social groups, these models can define digital poverty as falling below a minimum standard in one or more dimensions, including access to appropriate devices, reliable and affordable connectivity, digital skills and the ability to use essential online services (Barrantes Cáceres, 2007; van Dijk, 2006; Ragnedda & Muschert, 2013). Market-led broadband deployment has expanded overall connectivity, but provision remains uneven because rural, remote and low-density areas generally involve higher deployment costs and lower expected commercial returns (Malecki, 2003; Grubestic, 2006). Spatial models contribute to digital-poverty modelling by combining data on broadband availability and competition with socio-economic and demographic characteristics to identify populations and regions at risk of digital deprivation (Grubestic & Murray, 2004; Grubestic, 2006; Malecki, 2003). Econometric demand models and programme evaluations provide a complementary household-level component by assessing how prices, subsidies and other demand-side interventions affect broadband adoption. These

studies indicate that adoption is sensitive to prices, particularly where broadband is relatively expensive, but that evidence concerning the effectiveness of specific subsidy and adoption programmes is mixed; they also suggest that supply-side infrastructure investment alone may leave affordability, skills and perceived-relevance barriers unresolved (Galperin & Ruzzier, 2013; Hauge & Prieger, 2010, 2015).

Models intended to forecast digital-poverty risk can incorporate infrastructure-investment trajectories, technology-diffusion rates, data-pricing trends, educational attainment, age structure and government digital-inclusion policies. Diffusion studies indicate that income, urbanisation, existing network penetration, regulation and competition influence the adoption of successive generations of mobile and fibre-based technologies. Consequently, lower-income and less densely populated areas may fall behind without appropriate universal-service policies, regulatory interventions or public investment (Bohlin et al., 2010; Briglauer, 2014; Oughton et al., 2022). Data-pricing trends are important determinants of affordability and adoption, with evidence that lower broadband prices can significantly increase take-up where affordability constraints are severe (Galperin & Ruzzier, 2013). Educational attainment and age structure shape adoption, digital skills and patterns of use: higher educational attainment is generally associated with more diverse and potentially beneficial uses, while some older and less-educated groups face persistent barriers even where infrastructure is available (Hargittai, 2010; van Deursen & van Dijk, 2014). Finally, reviews and conceptual research on digital-inclusion policies suggest that interventions are more likely to be effective when they address multiple barriers—including devices, affordability, skills and ongoing support—whereas one-off or narrowly access-focused measures are unlikely to eliminate digital poverty on their own (Selwyn, 2004; Helsper, 2012; Hauge & Prieger, 2010).

8 CONCLUSION

This monograph has reviewed how broad-based poverty and selected domain-specific forms of deprivation, energy, transport, housing, water, food and digital poverty, are conceptualised, measured, modelled and, to varying degrees, forecast. Its central finding is that these domains share a common concern with households' ability to secure the resources, services and opportunities required for an acceptable standard of living, but differ substantially in their operational definitions, indicators, causal mechanisms, data requirements and analytical maturity. A common analytical framework can improve comparison and methodological learning across fields, yet it should not eliminate the distinctions that give each poverty domain its substantive meaning.

Across all the reviewed areas, poverty emerges as a multidimensional and dynamic condition rather than a simple consequence of low income. Income remains a fundamental determinant because it shapes households' capacity to pay for housing, energy, transport, water, food and digital connectivity. Nevertheless, income alone does not reveal whether services are physically available, whether infrastructure is reliable, whether housing and transport systems are suitable for individual needs, or whether households possess the capabilities required to convert formal access into effective use. Domain-specific poverty therefore arises through the interaction of household resources and needs with prices, infrastructure, spatial location, technology, environmental conditions and institutional arrangements. This interaction explains why households with similar incomes may experience substantially different forms and intensities of deprivation.

The comparison of indicators reinforces the conclusion that no single measure can identify all relevant dimensions or all affected households. Monetary and expenditure-based indicators provide transparent and comparatively accessible measures of affordability pressure, but may overlook households that suppress consumption or forego essential services. Subjective and consensual measures capture experienced hardship, although they are influenced by expectations, adaptation, social norms and survey design. Direct, infrastructural and spatial indicators identify inadequacies in service provision or physical access but do not necessarily demonstrate whether households can afford or effectively use the



services concerned. Composite and multidimensional indices provide a broader account of overlapping deprivation, but their results depend on choices concerning dimensions, thresholds, weighting and aggregation. Indicator selection is therefore not merely a technical decision: it determines which manifestations of poverty become visible and which households or places are prioritised by policy.

An important methodological conclusion is that identification, explanation, projection and forecasting must be clearly distinguished. Descriptive indicators measure observed deprivation, while econometric, spatial and classification models examine its correlates, determinants or geographic distribution. Longitudinal approaches add information on persistence, entry and exit, and therefore distinguish chronic from transient poverty. Microsimulation, computable general equilibrium, hydro-economic, land-use–transport and climate–crop models estimate outcomes under specified policy, price, demographic, technological or environmental assumptions. These are conditional projections rather than unconditional predictions. Genuine forecasting requires the estimation of future outcomes using information available at the time of prediction and an evaluation of predictive performance against observations not used to construct the model. Without temporal or out-of-sample validation, a model that successfully classifies current deprivation should not automatically be described as a forecasting model.

The maturity of forward-looking analysis differs markedly across the reviewed domains. Broad-based poverty has the most established household-level vulnerability tradition, including approaches that estimate the probability of future income or consumption falling below a poverty threshold. Energy-poverty forecasting is emerging, with several implemented dynamic-factor, panel and climate-informed applications, but much of the literature still consists of contemporaneous classification or conditional scenario analysis. Transport-poverty research has developed sophisticated accessibility, spatial and land-use–transport models, yet direct forecasts of future transport-poverty status remain limited. Housing-market forecasts are well established, but they are not consistently translated into forecasts of housing poverty among different household groups. Water and food research contains advanced biophysical, market and early-warning models, although the connection between system-level forecasts and household-level deprivation is often incomplete. Digital-poverty

forecasting remains comparatively underdeveloped and relies largely on infrastructure-deployment, technology-diffusion and broadband-adoption models rather than direct forecasts of multidimensional digital deprivation.

Despite these differences, a relatively stable set of cross-cutting predictive domains emerges. Household income, employment, demographic composition, health and existing assets influence the capacity to absorb shocks. Prices and financing conditions determine the affordability of essential goods and services. Infrastructure, dwelling characteristics, transport networks and spatial location shape physical availability and access. Climate and environmental conditions affect energy needs, water availability, food production, housing safety and transport reliability. Technology can reduce costs and improve access, but may also create new inequalities when adoption depends on capital, skills or digital connectivity. Finally, social protection, regulation, public investment and service governance mediate how system-level pressures are transmitted to households. The relative importance of these variables is domain-, indicator- and context-specific, and historically observed explanatory power does not guarantee future predictive performance.

A cross-domain perspective is particularly important where shocks and disadvantages overlap. Energy-price increases can simultaneously affect domestic heating and cooling, transport costs, food prices and housing affordability. Housing location influences energy requirements, transport dependence, digital infrastructure and access to food and services. Water scarcity can affect household expenditure, health, agricultural production and food prices. Digital exclusion can limit access to employment, education, benefits, transport systems, healthcare and information during crises. These interactions may create common pressures, cascading effects and feedback mechanisms through which an initial shock in one system produces deprivation in several others.

The evidence nevertheless does not support replacing domain-specific analysis with a single universal poverty score. An integrated approach should instead be modular. It should preserve clearly defined outcomes for each poverty domain while connecting them through shared household characteristics, macroeconomic conditions, spatial information and external scenarios. Such a framework would make it possible to identify both domain-specific vulnerability and cumulative disadvantage without assuming that all deprivations are



equivalent or fully substitutable. It would also reduce the risk of double-counting closely related indicators, such as housing quality and thermal adequacy, or income insufficiency and several expenditure burdens derived from the same household budget constraint.

Future research should consequently move from isolated retrospective indicators towards linked longitudinal and forward-looking systems. This requires harmonised household panels, expenditure data, administrative records, infrastructure and network information, geospatial data, environmental observations and credible projections of prices, incomes, demographic change and climate conditions. Models should report uncertainty, test sensitivity to alternative poverty thresholds and explicitly distinguish explanatory associations from causal effects and predictions. Forecasting studies should use rolling or genuinely out-of-sample evaluation, compare their performance with transparent benchmark models and examine errors across population groups and regions. Machine-learning methods can contribute by identifying nonlinearities and interactions, but their operational use requires interpretability, stability and safeguards against reproducing biases contained in historical data.

Table 1: Comparative synthesis of poverty concepts, indicators and analytical approaches

Poverty domain	Core definition	Key indicators	Key modelling and forecasting approaches
Broad-based poverty	Multidimensional and dynamic lack of the resources needed for an acceptable standard of living.	Income or consumption thresholds; poverty gap; material and social deprivation; MPI.	The most developed dynamic field: regression, transition and vulnerability (VEP) models can estimate future poverty risk, although results depend on thresholds and predictive validation.
Energy poverty	Inability to secure adequate domestic energy services because of affordability, access or housing constraints.	2M and M/2, LHC and fuel-poverty gap; inability to keep warm; arrears; housing quality.	Econometric, spatial and microsimulation approaches dominate. Forecasting is emerging, but household-transition forecasts and validated early-warning systems remain limited.
Transport poverty	Inability to afford or access the mobility needed to reach essential activities.	Transport-cost burden; accessibility and travel time; network coverage and reliability; unmet mobility needs; safety.	GIS, accessibility and land-use-transport scenario models are well developed, but direct, validated forecasts of transport-poverty status remain rare.
Housing poverty	Inability to obtain housing that is affordable, secure, adequate and suitable for household needs.	Housing-cost overburden or residual income; overcrowding; defects; tenure insecurity.	Price, rent and supply forecasting is mature, and microsimulation is widely used, but results are not consistently translated into household-level housing-poverty forecasts.

Poverty domain	Core definition	Key indicators	Key modelling and forecasting approaches
Water poverty	Inability to obtain sufficient, safe, reliable and affordable water for basic needs.	Water Poverty Index; availability and reliability; collection time; bill burden; water quality.	Physical scarcity and system-demand projections are advanced, while household affordability, distributional effects and governance remain weakly integrated.
Food poverty	Inability to secure adequate and acceptable food reliably and with dignity.	FIES; skipped meals; dietary diversity; affordability of a healthy diet; local food access.	Production, price and early-warning forecasts are relatively developed, but household forecasts need stronger links to local access, income and social protection.
Digital poverty	Inability to access, afford and effectively use digital technologies and essential online services.	Broadband, devices and data affordability; connection reliability; digital skills; use of essential services.	Most models forecast infrastructure or adoption rather than multidimensional digital poverty; skills, meaningful use and service outcomes remain difficult to predict.

For policy, the principal value of forward-looking poverty analysis lies in complementing, rather than replacing, observed indicators. Current poverty measures remain necessary for determining the extent of existing deprivation and evaluating whether households receive adequate support. Vulnerability and forecasting models can add an early-warning function by identifying households, regions or population groups that are not currently classified as poor but may become deprived following plausible changes in prices, income, infrastructure, climate or policy. Scenario models can further reveal the distributional consequences of proposed interventions and help compare preventive measures with ex-post compensation. Effective policy should therefore combine household-level income support with domain-specific measures addressing the underlying sources of deprivation, including housing renovation, affordable mobility, resilient water systems, food assistance, digital skills and connectivity, and accessible public services.

The overall contribution of the monograph is to demonstrate that poverty forecasting is best understood as an emerging family of approaches rather than a single established methodology. The reviewed fields offer complementary strengths: broad-based poverty research contributes dynamic vulnerability frameworks; energy and housing research highlights affordability and dwelling conditions; transport and digital research foreground accessibility and effective use; and water and food research demonstrates the importance of linking environmental systems with household welfare. Bringing these perspectives together provides a stronger basis for identifying emerging deprivation, analysing compound risks and designing policies that are anticipatory, distributionally informed and responsive to the specific mechanisms through which poverty is experienced.

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