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Supporting the support systems:

Integrating assistive technology access into aging policy frameworks

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2 Overview

Individuals who can obtain and effectively use assistive products, such as wheelchairs, hearing aids, and accessible software, are understood to have reliable access to assistive technology (AT). Such access is increasingly recognised as critical support in the context of global population ageing, where the prevalence of functional difficulties is rising and the demand for supportive solutions and services is expanding. In response, AT outcomes such as need, use, and unmet need are more often included in routine data collection systems, including censuses and household surveys. Similarly, dedicated surveys, such as the WHO Rapid Assistive Technology Assessment (rATA), have been successfully administered in dozens of countries, expanding the portfolio of available AT data.

Despite these advances, significant gaps remain in how these data are translated into forward-looking policy insights. Existing data sources are often single-wave and/or limited in their ability to capture how access varies across population groups and over time. Yet understanding how AT access differs by key demographic characteristics, such as age, gender, and socioeconomic status, is essential for identifying populations at higher risk of unmet need and for designing equitable interventions. Moving beyond static descriptions to anticipate how these disparities may evolve requires approaches that integrate population structure, demographic change, and projected outcomes.

Demographic forecasting methods offer a practical framework for addressing these challenges. By incorporating age structure, mortality patterns, and population projections, these approaches enable the estimation of how AT access and unmet need may change over time. When combined with disaggregated survey data, they also support intersectional analysis, allowing policymakers to examine how overlapping characteristics shape access to AT across the life course. In doing so, these methods help bridge the gap between available data and the evidence required for anticipatory, equity-oriented policy planning.

To these aims, this article presents how AT access data, increasingly captured through WHO survey tools and routine national data collection, can be analysed to produce reliable forecasts. Specifically, this article describes how these data can be used in a variety of demographic forecasting methods, including multistate life tables (MSLTs), both where multiple waves of data are available and through an adaptation that enables the use of single-wave data (Sullivan's method for MSLTs). While the latter relies on stronger assumptions, it provides a practical alternative in settings where repeated data collection is not yet feasible.

This article begins by describing the role of forecasting in the AT evidence sector. It then outlines five demographic forecasting methods, characterised by their data requirements and analytical outputs. Sullivan life tables are described in greater detail, with particular attention to their applicability in data-constrained contexts. The article then considers the types of insights these approaches generate and their relevance for policy and innovation in the AT sector, before discussing key limitations and concluding.

3 Background

Globally, population ageing emerges as a major driver of increasing demand for assistive technology (AT). However, access to AT is unevenly distributed in a country and is shaped by intersecting factors such as gender and socioeconomic status (SES). As populations continue to age, existing inequities in AT access, such as those experienced between men and women, or those of different social positions, will widen if they remain unaddressed. Further, continued under-representation of certain groups in research and a lack of intersectional analysis risk obscuring the scale and nature of these disparities and reinforcing inequitable access patterns over time.[1,2]

Forecasts of AT access and need are deeply interconnected with the development of broader ageing policies, such as those related to the labour market, long-term care financing, and addressing existing structural inequities, because they extend traditional demographic projections by incorporating trajectories of functional status and unmet need.[3] Whereas pension and retirement models typically rely on age structure, longevity, and labour participation trends, AT forecasts can add essential information about how older adults are likely to function in later life by drawing on transition probabilities,[4] age-specific prevalences, and life-course estimates[3] of functional difficulty and AT needs, integrated with population projections. These functional trajectories help policymakers anticipate whether future cohorts will live longer with difficulties or face widening inequalities due to unaddressed unmet needs. Such insights are directly relevant to policy decision-making on retirement age and pension planning, for example, as they indicate whether AT interventions could enable people to extend their working lives or whether worsening functional limitations may increase early retirement or disability pension needs.

AT needs are also not evenly distributed in society, and this variation is important to factor into future planning. For example, existing evidence indicates that women tend to have less reliable access to AT than men, with disparities being especially pronounced in LMIC contexts.[5–7] These gender differences are particularly salient in the context of population ageing. The 'feminisation' of ageing societies globally[8] is shaped by women living longer than men, while also being more likely to experience functional difficulties and disability in later life, as stated by the male-female survival paradox.[9] The relationship between gender and age has important implications for future AT demand. The growing number of older women living with disabilities means there is a need to plan for more older, female AT users in society. This relationship highlights that ageing-related AT needs cannot be understood without considering gendered life trajectories, patterns of disability, and differential access to resources across the life course. Socioeconomic status is also a key independent determinant of whether individuals seek[10] or can acquire[11,12] AT. SES also has a unique relationship with age: globally, the risk of experiencing poverty increases with age, and as global population ageing continues, the number of older adults experiencing poverty will also increase.[13] Access to AT during early- and mid-life is important to monitor, as it can enable participation in education and employment, further influencing SES trajectories (and subsequent AT access trajectories) across the life course. Gender disparities in later-life poverty are also prevalent, due to inequities occurring at younger ages.[13] A life-course perspective that takes SES into account strengthens the case for viewing AT access not only as a response to ageing, but as a determinant of how accessible 'healthy ageing' can be, and how it may be experienced, which is information vital for inclusive ageing policy development.

Forecasting AT access at all ages, therefore, has a critical role in shaping long-term planning for AT provision, particularly as ageing populations grow and patterns of need evolve.[14] More robust long-term planning can support policies and services that are responsive to demographic and epidemiological change. Yet existing projections are often hampered by fragmented data systems, inconsistent definitions,[1] and sparse or unrepresentative datasets. Improving the availability, comparability, and granularity of AT access data (and capturing important contextual factors[15,16] as well) would strengthen forecasts and enable policymakers to anticipate future AT demand with greater confidence and nuance, ultimately developing a better understanding of how to support older adults and disabled populations. Where in-depth data collection for this aim is prohibitively costly, statistical methods can be explored to augment or combine the fragmented data that do exist.

Demographic methods provide a practical means of addressing these limitations by linking available AT data to population structure and projected demographic change. By incorporating age patterns and enabling scenario-based estimation, these approaches allow existing data to be extended into forward-looking insights, even where datasets are incomplete or uneven. Their relative simplicity and accessibility further support their use in a wide range of settings, including those with limited analytical capacity. Importantly, these methods enable AT access to be examined as a life-course process shaped by intersecting characteristics. In doing so, they support a more policy-relevant interpretation of data, which connects observed patterns of access to future demand and highlights where unmet need is likely to persist or intensify.

4 Aims

This article aims to examine how demographic forecasting methods can uniquely contribute to the AT dataspace. Specifically, multistate life tables with adaptations of Sullivan's method (Sullivan life tables) are described in the greatest detail, as the method with the most utility in the AT evidence sector. Overall, this research intends to bring these flexible and understandable forecasting methods into the realm of AT research, where they can be used to maximise the value of sparse data for equitable AT provision planning.

5 Methods

5.1 Data sources

Demographic forecasting is increasingly feasible in the AT research space due to the growing availability of population-level data on AT access. A variety of forecasting methods can be used with data available from rATA surveys,[17] or any population-based surveys that collect data on functioning and AT use (and if available, AT unmet need), [2,18] to derive outcome prevalence. WHO definitions can be used to define AT outcomes across different surveys to ensure comparability; per WHO guidance, AT need is defined as self-reported difficulty in a functional domain for which an assistive product would provide support, combined with use and/or unmet need of products;

use is defined as current use of an appropriate product; and unmet need is defined as self-reported need for a product, regardless of current use.[19]

In this article, any single- or multi-wave survey from which AT outcomes (needing, using, or having unmet need for AT, among others) can be calculated is referred to as an AT survey. To support reliable forecasts, an AT survey should ideally be nationally (or sub-nationally) representative of the population of interest, cover the full adult age range, and have sufficient sample size in each covariate cell of interest to support disaggregated estimation.

Current and projected population data (the number of individuals alive at each age) as well as mortality data (the rate or number of deaths at each age) are widely available from the Institute for Health Metrics and Evaluation (IHME),[20] UN World Population Prospects,[21] and the Human Mortality Database.[22] National statistical office life tables may also be used where recent national data are available.

5.2 Demographic forecasting methods

A range of demographic forecasting approaches can be applied to estimate future AT access (indicated by self-reported functional difficulty, AT use, and unmet AT needs), under varying data constraints. This article describes five approaches that vary in complexity, data requirements, the factors they can account for, and the utility of the outcomes they produce. These approaches differ in their data requirements, the extent to which they capture population structure and dynamics, and the types of insights they generate, which are detailed in Table 1.

Approach 1: Aggregate prevalence rate extrapolation applies a baseline prevalence estimate to a population, assuming that the rate remains constant across the population. This approach requires only the total population size and an overall estimate of outcome prevalence, but does not account for population heterogeneity, demographic structure, or transitions between states. As a result, it provides a coarse approximation of the level of need, particularly in populations where the outcome varies strongly by age or other characteristics. For example, if the prevalence of glasses use in a country is estimated at 60%, this method would apply that proportion to the forecasted total population to estimate the number of future users.

Approach 2: Age-specific prevalence rate extrapolation advances the aggregate approach by disaggregating baseline estimates by age group and applying each age-specific rate to the corresponding population group, thereby introducing basic population structure (age). This requires age-disaggregated population and AT survey data and enables forecasts to reflect differences across the life course, including changes in the population's age composition. However, it still assumes constant prevalence within age groups and does not account for variation by other characteristics or changes in rates over time. Ebuenyi et al. approximate AT need based on age-specific prevalences of functional difficulty derived from single-wave data.[3] While their analysis focuses on current estimates, applying these age-specific rates to a projected population structure would constitute an example of age-specific prevalence rate extrapolation.

Approach 3: Disaggregated prevalence rate projection applies modelled prevalence estimates (rather than directly observed rates) to population data that are broken down by key characteristics such as age, sex, or locality. These modelled rates are typically derived from single-wave survey data using statistical methods (e.g., regression), allowing prevalence to vary across multiple covariates and better reflect intersectional differences in outcomes.

Common modelling choices include logistic regression for binary outcomes (e.g., AT use, yes or no) and multinomial logistic regression for three or more mutually exclusive states (e.g., no need, unmet need, and AT use). Where regression is not feasible, direct or indirect standardisation can be applied to transfer prevalence patterns from one population to another with a different composition. Intersectional effects are captured by including interaction terms between covariates (for example, sex × locality) rather than modelling each covariate additively, allowing prevalence to differ meaningfully for groups whose experience is not well represented by the average of single-characteristic effects.

The estimated relationships are then applied to externally derived population projections with the same structure, enabling forecasts to capture changes in population composition over time, including demographic ageing and shifts in group sizes. This approach improves on age-specific extrapolation by incorporating multiple dimensions of heterogeneity, producing more nuanced and policy-relevant estimates. It also allows for indirect standardisation across populations and can be adapted to different settings where only partial data are available. However, it assumes that the relationships between covariates and prevalence remain constant over time, does not account for mortality or survival differences between groups, and does not model transitions between outcome states or time spent in the outcome state. As a result, it cannot capture dynamic processes such as incidence, recovery, or changing risk over the life course. This approach, therefore, produces only prevalence-based projections; the lifetime and duration measures described below require additional data inputs and analytic steps.

Approach 4: Multistate life tables (MSLTs) are the most data-intensive approach considered here and incorporate age-specific transition probabilities across multiple states alongside mortality. Multistate life tables extend the 'basic' life table approach by adding states beyond 'alive' and 'dead' (i.e. accounting multiple states) to calculate the absolute and relative amount of time an individual will spend in a certain state over their lifetime, as well as the difference in life expectancy and time spent in a given state (i.e. a state-adjusted life expectancy).[23]

Transition probabilities between states are typically estimated from multi-wave panel data (a repeated survey of the same individuals) using Markov or semi-Markov models and usually assume time-homogeneous transitions within age intervals. Beyond requiring multiple waves, MSLTs require sufficient observed transitions in every cell of interest (combinations of age, covariate profile, origin state, and destination state) to estimate probabilities stably. This density requirement is often the binding constraint in AT applications, even when multi-wave data are available. Indeed, as most countries do not have multi-wave data that include questions about AT access,[2] methods for generating forecasting insights from single-wave data must be operationalised to incorporate AT access into long-term policy planning.

When considering AT access as a multistate process—in which an individual can transition back and forth between states of no need, unmet need, and AT use—the years spent in each state (i.e. with each outcome) can be calculated. The added benefit of this approach and MSLT outputs is that they offer considerable insight into patterns of advantage or disadvantage in a population, especially as these outputs can be uniquely calculated and compared across different 'covariate profiles' (i.e., a group within a population, defined by key covariates, such as rural females). Yet MSLTs require detailed transition data from multi-wave surveys and sufficient sample sizes to support disaggregation, making them challenging to implement in data-constrained settings.

Approach 5: Sullivan life tables (an MSLT adapted via Sullivan's method[24]) are an important forecasting tool for AT data. While true MSLTs require multi-wave data to derive transition probabilities, Sullivan's method adapts the life table approach to single-wave survey data, making it more feasible when multi-wave data are unavailable.[24,25] As single-wave surveys don't capture transitions, they cannot be straightforwardly used to generate transition probabilities needed to calculate true MSLTs. Instead, predicted state prevalences are calculated for each age and applied to the life table to calculate expected time in each state. These prevalences are typically generated from a regression model (for example, logistic regression for binary states or multinomial logistic regression for multiple mutually exclusive states), which stabilises estimates at fine age resolution and permits disaggregation by covariates of interest. Raw age-specific survey proportions can be used where sample sizes are large, though this is rarely practical once data are disaggregated.

This approach enables the derivation of duration-based measures useful in policy settings and when describing multi-state processes, and is particularly helpful in data-sparse settings. However, because it relies on prevalence rather than transitions, it assumes a stationary relationship between mortality and state occupancy. For example, this process assumes that the amount of time spent with unmet AT needs would not affect one's mortality risk.

In terms of data inputs, for each covariate profile, a Sullivan table requires the population size at each age (typically individual or 5-year age groups), mortality probabilities (or death rates, or number of deaths) at each age, and the prevalence of the outcome at each age. If the cohort is assumed to have a mortality schedule similar to the national average, national-level population and mortality data can be used, while the outcome prevalence would be derived from a representative household survey. The basic life table process and Sullivan's method have been described in detail for wider use.[26] In brief, the process calculates the life years lived at each age, both inside and outside the outcome state, with each person surviving to the next age contributing one life year (or 5 life years if the life table uses 5-year age groups). To calculate this, for each age interval, the life years lived overall are multiplied by the predicted prevalence of the outcome state. These values are added across all age intervals to get the total years lived in that state. Finally, the total years lived in that state are divided by the survivors to the next age to estimate the total lifetime spent with the outcome.

"Health expectancy" and "disability-free life expectancy" are commonly used MSLT/Sullivan terms for this key output measure. This measure is calculated as the sum of 'healthy' life years, or years spent without the key outcome, subtracted from the total life years an individual is expected to live. Healthy life years are generally equated to years spent without disability. However, these terms limit conceptual understanding in several respects. Disability and health are not interchangeable concepts, nor are they universally relevant to the variety of outcomes examined in AT research. Further, many of these outcomes can co-occur in theory (i.e. using a somewhat effective assistive product, and therefore having unmet need for a better one), whereas health/disability-adjusted life expectancies imply that years spent with disability cannot also be spent healthy – a premise that is inaccurate, and harmful to disseminate. To employ more appropriate terminology, this article suggests referring to this key measure simply as an out-of-state expectancy (i.e., time spent without the outcome). The underlying construct, expected time outside a defined state, has previously been described in the health expectancy literature as state-specific or condition-specific life expectancy. The term "out-of-state expectancy" is proposed here to retain continuity with that tradition while avoiding the health/disability framing that misfits many AT outcomes.

Table 1: Data availability and demographic forecasting methods

Available data	**Overall outcome prevalence + overall population size**	**Age-specific outcome prevalence + age-specific population size**	**Disaggregated population + disaggregated single-wave AT survey**	**Disaggregated population + disaggregated single-wave AT survey + disaggregated mortality**	**Disaggregated population + disaggregated multi-wave AT survey + disaggregated mortality**
Method	Aggregate prevalence rate extrapolation	Age-specific prevalence rate extrapolation	Disaggregated prevalence rate projection	Sullivan life table (adapted MSLT)	Multistate life table (true MSLT)
Incorporates					
Age structure	No	Yes	Yes	Yes	Yes
Mortality patterns	No	No	No	Yes	Yes
Covariates (e.g. gender, locality)	No	No	Yes	Yes	Yes
Outcome dynamics (e.g. states that vary with mortality risk)	No	No	No	No	Yes
Outputs					
Prevalence	Yes	Yes	Yes	Yes	Yes
Number of years lived with outcome	No	No	No	Yes	Yes
Share of lifetime with outcome	No	No	No	Yes	Yes
Transitions (incidence/recovery)	No	No	No	No	Yes
Inference	Descriptive	Descriptive	Model-based	Accounting-based	Dynamic model-based
Value add for AT policy planning	Aggregated outcomes	Age-specific outcomes	Further disaggregated outcomes	Lifetime and duration of outcomes	Trajectories and outcome dynamics

6 Applications

Multistate life table approaches provide more than simple extrapolated prevalence estimates, as they capture important aspects of population structure and outcome dynamics. Although they require more data, these inputs are increasingly available in many countries. MSLTs generate age-specific (and often sex-specific) outputs, allowing analysts to identify when particular states occur and how long individuals spend in them. This provides insights into the timing of need and the duration spent in those states, which can be translated into person-time measures and linked to economic analyses with broader policy relevance.

These methods also support equity and planning analyses by enabling comparisons across groups and settings. Differences in the share of lifetime spent in a given state can highlight inequities, including those that persist after accounting for factors such as longer life expectancy among women. Incidence can be directly estimated in true MSLTs or approximated in Sullivan life tables, providing information on new entries into states over time. These analyses allow investigators to test how outcomes change under different population or mortality scenarios and to simulate the potential impact of planned interventions, making them a flexible tool for forward-looking policy analysis.

Scenario casting can be done with all forecasts described here. In these analyses, an assumption about how the future population will change can be explored. For demographic forecasts, this is a straightforward process and typically involves ‘plugging in’ a separate set of population, mortality, or outcome prevalence data into the life table. These scenarios can be compared to derive policy insights for decision-making, particularly on how interventions may help alleviate unmet needs, or to test how an existing inequity may widen if no intervention is implemented. Innovators can also use scenarios to illustrate the anticipated impact of their work to funders.

7 Implications for Policy

Equity-focused policy requires forecasts that reflect disparities in access within countries and capture group-specific trajectories, rather than treating the population as a single pooled group. Disaggregated forecasts are essential for equity-focused policy, which requires that forecasts reflect disparities in access within countries and capture group-specific trajectories, rather than treating the population as a single pooled group. This improves the precision of evidence generation and decision-making by more accurately representing population groups.[27] The importance of disaggregated, intersectional data is well established in the Disability Data Advocacy Toolkit follow-up report,[28] which specifically highlights it as a key priority of Disabled People's Organisations. Sullivan's life table analysis can incorporate multiple intersectionalities by repeating it for different population groups and directly comparing them. Intersectional disadvantage can be more effectively addressed when evidence reflects these overlapping vulnerabilities. For example, women are more likely to experience poverty and disability,[6,29,30] particularly at older ages,[13] which has implications for financing and access to AT in ageing societies. Incorporating intersectional characteristics into forecasts enables policymakers to address structural inequities and design more targeted responses, including gender- and age-sensitive provision and financing mechanisms (e.g., gender-differentiated eligibility ages for subsidised provision or the inclusion of AT in widow's pension and old-age grant packages) to prevent inequities in AT access from widening.

The integration of survey data with vital statistics data in the Sullivan table allows policymakers to monitor changes in population structure alongside changes in key outcomes. Jointly considering these diverse datasets enables changes in both demographic composition (e.g., population ageing) and outcome prevalence to be reflected in updated estimates as new data or projections become available. While the approach itself is not dynamic in modelling transitions, it can be regularly updated with revised population, mortality, and outcome data, allowing policymakers to track and account for changes in outcomes as well as in the underlying population structure (e.g., triggering review of provision budgets when projected demand crosses a threshold, or flagging cohorts where unmet need is growing faster than population ageing would predict). Overall, forecasts support cross-sectoral coordination between health, social protection, and labour ministries, and sullivan tables are unusually well-suited to cross-sectoral use—the state duration output is straightforward to incorporate into person-year inputs for pension, care budget, and labour force participation models. Forecasting AT data means it can be incorporated in cross-sector planning as well.

Incorporating age structure is essential for designing policies that respond to population ageing, but age-specific forecasts also reveal a finding with broader implications: substantial AT need arises well before older age. Mobility, hearing, vision, and cognitive support needs accrue across the life course, driven by congenital conditions, injury, chronic illness, and working-age disability, and are not confined to later life. Forecasts that quantify the distribution of need by age can therefore challenge eligibility frameworks that implicitly treat AT as an ageing issue, and support the case for provision pathways that cover the full life course.

For older populations specifically, age-specific estimates of when need typically onsets, and how long individuals spend with unmet need before accessing a product, allow policymakers to anticipate both the timing and scale of demand. Concrete policy responses include lowering or removing age thresholds for subsidised provision where need emerges earlier than current eligibility assumes; aligning AT provision with other age-triggered entitlements such as pension enrolment or geriatric health assessments to reduce access delays; and investing in earlier awareness and screening interventions so that onset of need is detected closer to the point at which it arises.[31,32] Forecasts showing widening gaps between age at onset of need and age at first access can further indicate the need for system-level redesign.

The dynamic nature of AT need, captured through transitions between states over the life course, highlights the importance of flexible and responsive systems. Multistate approaches reveal how individuals move between need, use, and unmet need, providing a more realistic picture of demand over time. This lens supports the design of adaptive service models, such as lending libraries or modular provision systems, that can respond to changing needs.[33] Recognising these dynamics is key to aligning service delivery with real-world patterns of need.

Current planning remains constrained by limitations in available data, underscoring the need for more inclusive and comprehensive data collection. Expanding intersectional representation, incorporating multiple measures of key constructs, and improving coverage of underrepresented groups would enhance the relevance and precision of analyses.[1] Greater harmonisation of measurement (such as adopting standardised survey modules) and investment in multi-wave data collection would reduce uncertainty and strengthen future forecasting capacity. Embedding these priorities within national monitoring frameworks can improve both the technical robustness of projections and their policy impact. In the interim, policymakers can draw on consistent directional patterns, plausible ranges of demand, and identification of high-risk groups to inform decision-making. But at the same time, stakeholders should advocate for improved data systems (e.g., embedding AT modules, such as those developed for the rATA, in next-cycle national household surveys, and prioritising countries with no current AT data for initial investment) to support more accurate and equitable planning in the future.

8 Implications for Innovation

Innovators also have a role in reducing unmet need for AT, and demographic forecasts can help identify where they may make the most significant contribution. Populations experiencing disproportionate prevalence and/or unmet need (particularly those projected to grow with population ageing) highlight high-growth market segments where existing solutions fall short and future demand is likely to increase. Importantly, populations with high unmet need may be under-served precisely because they are unprofitable under conventional market logic (e.g., remote and rural populations in LMICs); globally, most unmet AT needs are driven by cost.[5] Forecasts can identify these segments, but the implication for innovators isn't always the market opportunity, and rather that pooled procurement, cross-subsidy, or concessional financing may be needed to unlock the market.

Variations in the timing and duration of AT need further indicate demand for long-lasting, reusable products.[33,34] The life course perspective used in Sullivan life tables further supports the development of modular, upgradeable, and easily repairable solutions that adapt as users' needs change. With disaggregated, group-specific evidence, innovation can move beyond designing for an "average user" and instead reflect intersectional needs,[28] supporting a shift toward evidence-driven product development rather than assumption-based approaches that are often common in design processes.

9 Limitations

Forecasts share the same limitations as the datasets on which they are based. Can't disaggregate by factors that weren't collected in the survey to begin with.

Life table estimates using IHME population and mortality data will be more reliable where countries have more recent administrative data collection (which is used to inform the IHME estimates), and where the AT survey was carried out at a similar time. Mortality probabilities from IHME are also available in 5-year age intervals, which is a standard level of granularity for life tables. However, this process requires the assumption that mortality is constant across each age interval, whereas estimates would be improved if continuous mortality probabilities could be used.

IHME vital statistic data are not typically available disaggregated by all covariates that may be included in the AT survey, so the absolute number of individuals experiencing each outcome can't be estimated, which is a result that is highly relevant to policy planning; rather, findings are limited to the amount and share of person-time spent in states among particular groups. However, these person-time estimates can still be applied to more detailed vital statistic data in future (what is typically available in an up-to-date census), should it become available.

Population-based AT surveys may use household sampling designs that exclude institutionalised populations, thereby underestimating the prevalence of AT needs and leading to a disproportionately high estimate of mortality probabilities (which alternatively do include institutionalised individuals, who tend to have higher mortality than the general household population).

Sullivan's life tables also have specific limitations. Because they are based on single-wave data, they cannot tell whether individuals previously experienced a particular state, or for how long they have been in their current state—changes over time can only be approximated, not directly observed. Sullivan tables do not model transitions between states, and so cannot capture processes like incidence and recovery. In contrast, true multistate life tables explicitly model transitions between states using multi-wave data, providing a more dynamic and realistic picture of how needs evolve over time. They also handle uncertainty more consistently by incorporating it directly into the estimation of transitions and outcomes. Sullivan's method includes multiple sources of uncertainty, but these are often not fully carried through to the final estimates, which can lead to underestimation of uncertainty. Despite this, Sullivan's approach remains useful because it is simpler, easier to interpret, and feasible when multi-wave data are not available.

10 Conclusion

Embedding AT forecasts within ageing policy frameworks strengthens cross-government strategies by linking functional capacity, enabling environments, and social protection systems; enabling policies that address both the economic and capability-related dimensions of ageing; and ensuring that AT provision policies are responsive to the dynamic functional realities of ageing populations.

This article demonstrates how Sullivan's method can enable single-wave AT data to be represented in long-term policy planning. Importantly, the life course framing highlights the prevalence, duration, and timing of outcomes; uniquely estimated for different population groups to accommodate intersectional variation; and with straightforward scenario forecasting. Through the use of life tables, a life-course perspective is used to highlight that supporting ageing populations also means reliable AT access is needed in earlier years. Advocacy for increased AT provision among older adults should not obscure needs at other ages. Though the urgency of population ageing will motivate many governments to expand AT provision, this should be done with policies that are relevant to all ages of AT users.

This article finally illustrates the compromises inherent in intersectional demographic modelling. Disaggregation by age, sex, and further characteristics often result in small sample sizes that limit confidence in estimates. The extent to which data augmentation can attenuate this limitation deserves further research. This limitation also reinforces the need for larger, more representative surveys including AT users. Still, the timing and duration outputs demonstrate the utility of Sullivan tables to conceptualise and translate the process of AT access into insights that inform long-term policy planning, particularly where data are sparse.

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