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Extending intersectional multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) to study individual longitudinal trajectories, with application to mental health in the UK

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A R T I C L E I N F O

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A B S T R A C T

The intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) approach is gaining prominence in health sciences and beyond, as a robust quantitative method for identifying intersectional inequalities in a range of individual outcomes. However, it has so far not been applied to longitudinal data, despite the availability of such data, and growing recognition that intersectional social processes and determinants are not static, unchanging phenomena. Drawing on intersectionality and life course theories, we develop a longitudinal version of the intersectional MAIHDA approach, allowing the analysis not just of intersectional inequalities in static individual differences, but also of life course trajectories. We discuss the conceptualization of intersectional groups in this context: how they are changeable over the life course, appropriate treatment of generational differences, and relevance of the age-period-cohort identification problem. We illustrate the approach with a study of mental health using United Kingdom Household Longitudinal Study data (2009–2021). The results reveal important differences in trajectories between generations and intersectional strata, and show that trajectories are partly multiplicative but mostly additive in their intersectional inequalities. This article provides an important and much needed methodological contribution, enabling rigorous quantitative, longitudinal, intersectional analyses in social epidemiology and beyond.

1. Introduction

The intersectional MAIHDA approach is a simple but effective way to consider differences in individual outcomes between different sociodemographic intersectional groups (Evans et al., 2018). Since its introduction, the approach has been used throughout the health sciences (Beccia et al., 2021; Evans et al., 2023; Evans and Erickson, 2019; Holman et al., 2020; Moreno-Agostino et al., 2023b; Persmark et al., 2020; Zubizarreta et al., 2022) as well as in other social science disciplines such as environmental justice (Alvarez et al., 2022; Alvarez and Evans, 2021) education (Keller et al., 2023; Prior et al., 2022) and the sociology of sexual identification (Silva and Evans, 2020). Intersectional MAIHDA provides a useful approach to quantify intersectional inequalities, understanding the extent to which these are additive and multiplicative, and recognizing that inequalities can be conceptualized in terms of differences in averages and variances around those averages, whilst (partially) correcting for multiple testing (Bell et al., 2019). It has been shown to outperform alternative methods (Bell et al., 2019; Mahendran et al., 2022).

So far, all implementations of the intersectional MAIHDA approach that we are aware of have conducted cross-sectional analyses. Yet, there is increasing availability of longitudinal data on health and other social science outcomes, as well as conceptual and theory-driven interest in life course approaches. These data provide opportunities to further understand intersectional differences, including intersectional trajectories for strata over time, and thus how stratum outcomes change, and whether inequalities worsen or improve, over the life course. That includes consideration of how (dis)advantage accumulates over the life course (O'Rand, 1996), and the scarring effects of particular events, all of which can be intersectionally patterned (Dressel et al., 1997; Ferrer et al., 2017; Holman and Walker, 2021).

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The use of longitudinal data also presents theoretical challenges regarding how identity-positionality intersections are defined. The conceptual basis of intersectional theory lies in social justice, and understanding the ways populations at the intersection of multiple systems of marginalization and oppression may experience extra or unique burdens or harms, beyond only (additive) summations of their disadvantages. Approaching intersectionality from a longitudinal perspective raises new conceptual challenges, such as whether individuals' identities change throughout their lives. Many of the things we consider to be central to individuals' intersectional identities may be relatively stable (such as ethnicity). Others, by definition, change regularly over the life course (such as age). How we choose to model the time-varying nature of different aspects of individuals' identities should reflect the ways we understand identity formation, and the effects on (health) outcomes of dynamic social processes for people with those identities (Hockey and James, 2017).

So, despite its demonstrable rigour (Bell et al., 2019; Mahendran et al., 2022) and growing popularity, the MAIHDA approach has not previously been extended and applied to longitudinal data settings. Yet, there is widespread availability of longitudinal data and theory emphasising the dynamic nature of intersectional inequalities. This paper fills that conceptual and methodological gap.

We present an extension to the intersectional MAIHDA approach that allows individuals to have different age *trajectories*, and for those differences to be modelled by intersectional strata. We will also include generation (based on birth year) in the definition of those intersectional strata – this could not be done with cross-sectional data due to its exact collinearity with age. We illustrate the approach using data from the UK Household Longitudinal Study (UKHLS), considering intersectional differences in individual mental health life course trajectories. This is a relevant example, given previous literature exploring intersectional inequalities in mental health (e.g. Balloo et al., 2022; Evans and Erickson, 2019; Moreno-Agostino et al., 2023b), and a separate literature exploring (average) life course trajectories in mental health (e.g. Bell, 2014; Beller, 2022; Blanchflower and Oswald, 2008).

Like cross-sectional MAIHDA, the approach presented here is exploratory and descriptive. But when combined with theory about particular intersectional strata and processes of (dis)advantage, especially in combination with in-depth, qualitative methods, the approach has great potential for uncovering and understanding complex inequalities through the life course.

This article proceeds as follows. First, we consider some of the conceptual and then methodological issues that underlie any attempt to apply the MAIHDA approach longitudinally. We then outline a longitudinal, intersectional MAIHDA approach, extending cross-sectional MAIHDA. Finally, we illustrate this extension with an application to individual mental health trajectories in the UK.

2. Intersectionality and the life course – critical theoretical frameworks

Intersectionality is a framework that emerged in Black feminist and critical race scholarship (Crenshaw, 1991; Hill Collins, 2008) to make visible unique forms of discrimination experienced by Black women. In legal cases, Black women who faced employment discrimination found themselves having to argue their experiences resulted either from their *race* (countered by employers with evidence of employment of Black men) or their *gender* (countered by employers with evidence of employment of white women) (Crenshaw, 1989). It was the unique intersection of race and gender where the discrimination occurred. Making visible the invisiblised experiences of such "hidden" populations, simultaneously considering multiple axes of marginalization, and critiquing and calling for transformation of systems of oppression and inequity have been core to intersectional scholarship since its inception. Since then, the framework has expanded to address additional axes of identity and marginalization, include multiple methodological approaches, and evaluate numerous outcomes and inequalities (Hill Collins, 2008).

McCall (2005) identifies three broad approaches to intersectional scholarship: anti-categorical, intracategorical, and intercategorical approaches. *Anti-categorical* scholarship critiques the very project of categorisation, identity formation, and labelling. Scholarship of this type has had a profound effect on research by encouraging caution and reflection when we use labels, such as awareness that gender is neither fixed nor binary. *Intracategorical* scholarship, true to the original project of highlighting the experiences of Black women, focuses on populations at particular intersections of interest, and highlights (using qualitative, quantitative, or mixed methods) their experiences or outcomes. Finally, *intercategorical* scholarship, which is often quantitative, provisionally adopts categorical labels to assess inequalities across population intersections. Our present study aligns with and contributes to this intercategorical approach.

In parallel, a life course epidemiology perspective has developed, that highlights that "biological and social factors throughout life independently, cumulatively and interactively influence health and disease in adult life" (Kuh et al., 2003:778; Ben-Shlomo and Kuh, 2002; Merlo, 2011). Health is thus something that is produced not just through static determinants, but also through dynamic processes that accumulate through the life course. Such an approach often considers how health can be defined by unhealthy exposures at "critical periods" of the life course, and how particular groups may have more resilience and vulnerability to exposures both throughout and at different points in the life course. Clearly, then, health inequalities are likely to be produced at particular points in the life course, and between different generational and intersectional groups, through these life course processes. Further, a longitudinal life course perspective has implications for monitoring and evaluating policies and interventions that might affect intersectional health inequalities, suggesting a need for tracking intervention/policy effectiveness over time, across the life course.

Recent literature underscores the importance of integrating intersectionality with a life course perspective to elucidate the temporal dimension of intersectional inequalities (Brotman et al., 2020; Ferrer et al., 2017; Holman and Walker, 2021; Moen and Miller, 2022). Termed the 'intersectional life course' perspective, this approach seeks to embed pivotal life course concepts—roles, life stages, timing, trajectories, transitions, and temporal patterns of inequality—within the intersectional paradigm (Holman and Walker, 2020). These concepts, when viewed through the lens of both frameworks, are complementary (*ibid.*). Similarly, Ferrer et al. (2017) delineate four elements of an intersectional life course perspective: timing and structural forces, local and globally linked lives, identities and categories of difference, and agency, domination, and resistance. These elements collectively aim to elucidate the structural, personal, and relational processes that shape the lives of diverse groups of older adults. Recognizing that inequalities are multifaceted in their interconnections, temporal dynamics, and social contexts, it becomes crucial to adopt methodological approaches that capture these complexities. A notable methodological gap exists in analysing intersectional inequalities in *trajectories*, especially using the MAIHDA approach – a gap this paper aims to fill. Such an approach can not only reveal how intersectional inequalities change with the ageing process but also delineate the distinct effects of cohort and generation in producing them.

3. Practical concerns when extending MAIHDA longitudinally

In the online Appendix 2, we outline the intersectional MAIHDA approach using cross-sectional data (see also Evans et al., 2024b). Increasingly, longitudinal data has become more common and easily accessible, and so the need to extend this MAIHDA approach for use in longitudinal data is clear. However, there are several issues that longitudinal data poses, both technical and theoretical, which need to be addressed in a longitudinal MAIHDA approach, whilst maintaining the empirical advantages of MAIHDA and fidelity to the conceptual frameworks highlighted above. In this section, we identify three key concerns that are raised when using panel data that are not of consequence when using cross-sectional data: (1) whether intersectional identities are fixed or can change over time; (2) the nature of age in intersectional identities; and (3) the role of the variables age, period and cohort, both in defining intersections, and in requiring a solution to the age-period-cohort identification problem (Bell, 2020).

3.1. Are identities fixed?

When analysing cross-sectional data, the dynamic nature of social variables is not typically considered. Data measure only one point in time, and we take the state of individuals at that time as defining individuals' identities (or circumstances). Things are more complex in reality, as evident in longitudinal data, because sometimes those variables change value across the life course. This is not always true – many variables that capture individuals' identities are relatively stable, either not changing or changing rarely (where a change implies something very specific about that individual that we might want to capture). For instance, if an individual reports their sex/gender changes over time, this may indicate a gender transition, and we might code that individual as transgender and apply that categorisation retrospectively throughout their observations in our dataset. Similarly, if we were including sexuality as an intersectional variable, it is plausible that an individual might 'come out' between waves in the survey, meaning they might be classified as heterosexual/staight in initial waves but non-heterosexual/non-straight in later waves. In this instance, even if the occasion of coming out does not align with the individuals' identity actually changing, it may align with how others view them, how they express themselves, and consequently what forms of discrimination they may experience.

The extent to which identities are fluid will depend on the nature of the data, the precise questions respondents are asked, and the nature of the research questions at hand, as well as the social context in which the data is being collected. In some cases, researchers may treat identities as non-changing (even if there is evidence of change) for theoretical or empirical reasons, or to manage complexity. In other cases, the dynamic nature of intersectional identities will be central to the research questions being asked, and the modelling approach will need to reflect that. Conversely, often the number of identity changes in a dataset will be limited, making a study of such changes unfeasible.

3.2. Age groups, or age trajectories?

One variable that will not remain static over the course of the sample is age – for each wave that passes, individuals will get older. This raises an interesting question of how we think of age as a variable that forms intersectional identities: do individuals transition through different intersectional identities as they age, or do they remain in the same intersectional identity, which experiences an age trajectory over time? The answer is likely both – however, transitions through identities is something that happens gradually, and not in a discrete way, such that individuals transition at particular ages into new identities (although there are more discrete life course transitions that may align approximately to particular ages, such as starting a family or retiring). These gradual transitions may in part be shared with others of the same age at similar times. Clearly age changes people and how others treat them, such that we would expect their outcomes to vary over the life course. Moreover, the meaning of an intersectional label, and the identity associated with that meaning will also change over the life course. However, following a life course perspective, it makes sense to us to think of people in a particular intersectional identity travelling through their lives, with their age-related identity gradually shifting in a way that is in common with their intersectional cohort group. This relates to the previous point about the fluidity of intersections; age is fundamentally different to many other intersectional labels which are, generally, rarely-changing, even if the meaning behind those labels changes over the life course. It is also different in the sense that age, for many health outcomes, is likely to have effects that are strongly biological in their nature, as well as produced through social processes (to a greater extent, generally, than other often-used intersectional variables). It therefore makes sense to think of age differently, as a trajectory that individuals follow over time, rather than defining intersectional identities themselves.

Where data are repeated cross-sections, with a different sample of individuals in each wave (as opposed to panel data which following the same individuals), a similar approach could be taken. Each individual will be measured at only one age, but this still allows the estimation of an average population age trajectory that could vary by intersectional strata. The same applies to other forms of longitudinal data (birth cohorts, survival data, etc.). We reflect on these possibilities in the paper's conclusions.

3.3. Age-period-cohort (APC) and the identification problem

Alongside age, there are two other ways to classify change over time, which may be useful to consider when constructing analytic groupings of intersectional identities. First, change can happen year-by-year in the course of history, such that particular events can affect an individual's outcome (period effects). Second, historical events can have long-lasting effects, particularly for those in their formative years, for whom those effects stay with them through their lives (cohort effects). In the online Appendix 3, we discuss these ideas in more depth. Here, we will summarise as follows:

- Age, period and cohort cannot be fully considered in cross-sectional analysis, since there is no variation in period, and age and birth-year are exactly correlated.
- Generation/cohort is likely an important determinant of intersectional inequality, and should be included when defining intersectional strata in longitudinal analysis.
- The APC identification problem makes it difficult to separate age, period and cohort effects (see Bell, 2020). However, we can use a model that instead identifies "cohort careers", to see how different cohorts have different life course trajectories (Fosse and Winship, 2023). The approach includes both cohort and age in the model; the parameter(s) associated with age represent a combined trajectory of the life cycle (produced by a combination of age and year effects). Similarly, the parameter(s) associated with cohort represent social change, produced by a combination of cohort and period (Fosse and Winship, 2023). While this does not disentangle APC effects per se, it allows for a sound conceptualization of them without relying on strong assumptions.

4. A longitudinal MAIHDA approach

The approach outlined here attempts to incorporate the above ideas, and the intersectional life course perspective (Ferrer et al., 2017; Holman and Walker, 2021), with the intersectional MAIHDA approach (outlined in online Appendix 2). Panel data measures individuals on multiple occasions, meaning that the unit of observation is not individuals, but the repeated occasions on which they are measured. As such, any panel analysis will have, as its lowest level of measurement, the occasion – that is the particular instance in which a particular individual is measured. The starting point for any longitudinal MAIHDA approach, then, is extending the two-level structure of standard MAIHDA models by adding an occasion level as a new level 1, leading to a 3-level structure as shown in Fig. 1, with occasions (level-1) nested in individuals (level-2), which are in turn nested in intersectional strata (level-3). This structure is appropriate where intersectional strata are conceived as non-changing (we discuss approaches where strata are

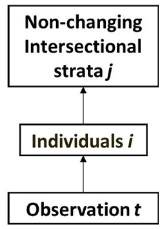

Fig. 1. Longitudinal MAIHDA structure, where intersectional strata are theorised as being time-invariant for individuals.

considered changing in the conclusions).

Based on the logic above, we would not include age to define our strata – age would be accounted for in the fixed part of the model as specified below. We would, however, include cohort, since this is non-changing within individuals, and there are clear reasons why we would expect it to be important from the point of view of identity formation, and potentially produce interesting inequalities, for instance in outcomes such as mental health (Bell, 2014; Moreno-Agostino et al., 2023a). Those cohorts would need to be grouped in a way that was theoretically informed – for instance we could group by commonly understood cohort classifications (Baby Boomers, Gen-X, Gen-Y, etc). Whilst there is some controversy over the extent to which these discrete groupings are meaningful (Rudolph and Zacher, 2022), as with other variables that define strata, we want to group in a way that expresses intersectional identities that reflects peoples' experiences of their own identities and others. Of course, identities are much more complex than can be specified in any model.

As with cross-sectional MAIHDA, the longitudinal MAIHDA approach uses two models. However, these are random-slopes (rather than random-intercepts) multilevel models. The first model can be specified as follows:

$$\text{Health}_{tij} = \beta_0 + \beta_1 \text{Age}_{tij} + v_{0j} + v_{1j}\text{Age}_{tij} + u_{0ij} + u_{1ij}\text{Age}_{tij} + e_{tij} \tag{1}$$

Here, β_1 is the overall linear effect of age, which we recommend centring (e.g., on its sample mean) so that the intercept β_0 provides an estimate of Health_{tij} for mean-aged individual. We could extend the model to include non-linear age effects (e.g., by entering age as a polynomial) but here we stick with a linear effect for simplicity. In the random part of the model, at the stratum level (level-3), v_{0j} allow the intercepts to vary, whilst v_{1j} allows the age slope to vary, across intersectional stratum j. The between-stratum residuals capture how strata-specific trajectories vary around the overall age trajectory line (given by β_0 and β_1). As such, the model allows for stratum-level variability not just in the mean level of health, but in the age trajectories of health across the life course. The same is true at the individual level, where u_{0ij} and u_{1ij} allow individual-specific age trajectories within intersectional strata. This variability allows us to capture the heterogeneity of age trajectories experienced within the same intersectional strata. Finally, the level-1, occasion level residual e_{tij} captures variation occurring within individuals between occasions, and can be thought of as a measure of within-individual volatility – that is how much we would expect an individual's measurements of health to vary away from a smooth trend line.

The residuals highlighted above are allowed to vary according to the usual bivariate Normal assumptions of a random slopes multilevel model (note that it is important to specify the covariance between intercepts and slopes in these distributions, which is not the default in some software):

$$\begin{gathered}
\begin{pmatrix} v_{0j} \\ v_{1j} \end{pmatrix} \sim \text{N}\left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{v0[1]} & \\ \sigma_{v01[1]} & \sigma^2_{v1[1]} \end{pmatrix} \right\} \\
\begin{pmatrix} u_{0j} \\ u_{1j} \end{pmatrix} \sim \text{N}\left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{u0} & \\ \sigma_{u01} & \sigma^2_{u1} \end{pmatrix} \right\} \\
e_{tij} \sim \text{N}\left(0, \sigma^2_e\right)
\end{gathered} \tag{2}$$

In a random-slopes model, we do not estimate a single random effect variance at each level. Instead, the three terms that are estimated at each of the higher levels can be combined to form variance functions (Bullen et al., 1997), which expresses how the variance at that level varies with age. For instance, the total stratum-level (level-3) variance will equal:

$$\text{L3 variance}_{[1]} = \sigma^2_{v0[1]} + 2\sigma_{v01[1]}\text{Age}_{tij} + \sigma^2_{v1[1]}\text{Age}^2_{tij} \tag{3}$$

Similarly the level-2 variance (within strata, between individuals) will equal:

$$\text{L2 variance} = \sigma^2_{u0} + 2\sigma_{u01}\text{Age}_{tij} + \sigma^2_{u1}Age^2_{tij} \tag{4}$$

The level-1 variance remains constant: σ^2_e.

These quadratic equations allow us to plot how the variance at each level varies by age. The total stratum-level variance measures the extent of intersectional inequalities, and how these widen or narrow over the life course. These can be meaningfully compared to the extent of total variance within stratum groups but between individuals, and the extent of within-individual variance (levels 2 and 1 respectively). That is, we can see the extent to which strata are predictive of age trajectories, compared to other possible individual- and occasion-level differences.

Because these variances functions are more complex than single numbers, we cannot calculate a single invariant Variance Partitioning Coefficient (VPC), measuring the proportion of variance at a higher level, as in cross-sectional MAIHDA (see online Appendix equation A3). However, we can calculate separate intercept and slope VPCs, to consider the extent to which individual differences in intercepts, and individual differences in slopes, are produced through intersectional inequalities:

$$\begin{gathered}
\text{Intercept VPC} = \frac{\sigma^2_{v0[1]}}{\sigma^2_{v0[1]} + \sigma^2_{u0}} \\
\text{Slope VPC} = \frac{\sigma^2_{v1[1]}}{\sigma^2_{v1[1]} + \sigma^2_{u1}}
\end{gathered} \tag{5}$$

It is important to note that the value and interpretation of the intercept VPC will be dependent on how age is centred – if age is uncentred, the VPC for the intercept will be calculating the VPC at age zero, likely outside the range of the data and not substantively meaningful. If mean-centring age, the intercept VPC would calculate the extent of intersectional inequalities, as a proportion of all individual difference, for the average-aged person. The slope VPC would define the extent to which the intersectional groupings explain the between-individual differences in the slopes of the individual age trajectories, and is unaffected by centring.

As with the cross-sectional MAIHDA approach, the longitudinal approach builds on the first model by adding the additive effects of the intersection-defining variables into the second model. However, here we additionally include interactions between age and those intersection-defining variables. As such, equation (1) above is extended to:

$$\begin{gathered}
\text{Health}_{\text{tij}} = \beta_0 + \beta_1 \text{Age}_{\text{tij}} + \sum_1^k \gamma_k \text{X}_{\text{kj}} + \sum_1^k \delta_k \left(\text{X}_{\text{kj}}\text{Age}_{\text{tij}}\right) + \\
v^*_{0j} + v^*_{1j}\text{Age}_{\text{tij}} + u_{0ij} + u_{1ij}\text{Age}_{\text{tij}} + e_{tij}
\end{gathered} \tag{6}$$

Here, X_{kj} represents k stratum-level dummies for the strata-defining variables – which might include sex/gender, ethnicity categories, education categories (as in cross-sectional MAIHDA) as well as dummies representing cohort groupings. These are included as main effects γ_k, and interacted with age with coefficients δ_k, to ensure any additive differences in both intercepts and age trajectories are included in the model. As such, two-way interactions involving age are conceived of as "additive" in this formulation of intersectional differences, but they can be analysed and interpreted as any other interaction in a regression model. The model in equation (6) includes coefficients that explain stratum-level variance in both the intercept (the main effects) and the age slopes (the interactions with age). The distributional assumptions of this model are the same as in the first model, and we would expect the estimates to be the same except at level 3, where the fixed effects will explain some of the variance resulting in different variance estimates.

$$\begin{pmatrix} v^*_{0j} \\ v^*_{1j} \end{pmatrix} \sim \mathrm{N}\left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2_{v0[2]} & \\ \sigma_{v01[2]} & \sigma^2_{v1[2]} \end{pmatrix} \right\} \tag{7}$$

We can calculate the variance function associated with the stratum level again:

$$\text{L3 variance}_2 = \sigma^2_{v0[2]} + 2\sigma_{v01[2]}\text{Age}_{tij} + \sigma^2_{v1[2]}\text{Age}^2_{tij} \tag{8}$$

The comparison of the stratum-level variance functions between the two models allows researchers to see the extent to which age-specific intersectional differences in the outcome variable are explained by additive intersectional variable effects, as opposed to multiplicative effects. If inequalities are patterned additively (and the level 3 variance is low in model 2), this indicates relatively universal or consistent patterns (for instance, if gender differences remained fairly stable across other axes of comparison). If the inequalities are not sufficiently accounted for by additive main effects, then this implies that some strata (at least) break with the universal patterns described by the additive terms (Evans et al., 2024a).

In cross-sectional MAIHDA, we can measure the Proportion Change in Variance (PCV) – the proportion of strata-variance that is accounted for by additive main effects (see online Appendix equation A5). In longitudinal MAIHDA, because the stratum-level variance varies with age, there is no single PCV value. Instead, and similar to the VPC, we could include an intercepts-only and slopes-only version of the PCV. The intercepts-PCV would tell us the extent to which the additive effects of the intersectional variables explain the variability of intersectional groups for the mean-aged person (assuming age has been centred). Similarly, the slopes-PCV tells us the extent to which the differences in age trajectories between the strata are explained by the intersectional variables' interactions with age.

$$\begin{aligned} \text{Intercept PCV} &= \frac{\sigma^2_{v0[1]} - \sigma^2_{v0[2]}}{\sigma^2_{v0[1]}} \\ \text{Slope PCV} &= \frac{\sigma^2_{v1[1]} - \sigma^2_{v1[2]}}{\sigma^2_{v1[1]}} \end{aligned} \tag{9}$$

Past experience of the cross-sectional case suggests that VPCs in the null model tend to be smaller than 10%, reflecting the fact that there is usually significantly more variation in outcomes within intersectional groups than between. PCVs are generally around 90%, reflecting that we would often expect much intersectional variance to be additive (Evans et al., 2024a). We would generally expect to see something similar for our intercept VPCs and PCVs, although we would not assign labels to thresholds for what constitutes a "large" or "small" effect, since this will depend on the nature of the outcome variable and the intersections specified. With slope VPCs and PCVs, the same applies, although in some situations, this may be more variable where the initial slope variance is relatively small.

Regarding the prediction of specific intersectional strata, we are predicting trajectories rather than means. Again, we could rank these by intercepts and by slopes, where that is meaningful (and that allows useful comparison to the cross-sectional case). Alternatively, it will often make sense to plot the trajectories, and use colours and labels to highlight notable strata in those plots.

Such estimates can have important potential policy implications, drawing on life course theories. As well as providing a measure of the universalism vs specificity of intersectional inequality (Evans et al., 2024a), longitudinal MAIHDA allows consideration of the extent to which inequalities are generally fleeting, lasting only for a particular age grouping, or enduring. Each of those two would have different policy implications – for example, intervening with a stratum that is likely to become less disadvantaged with age might not be appropriate; intervening with a stratum that is likely to become more disadvantaged might be appropriate, even if they are not currently disadvantaged.

There are a few additional issues to consider:

1. Here we have included just a linear term for the age trend. In some cases, including the example that follows, a more complex functional form may be needed (e.g., a quadratic or cubic polynomial), whereas in other cases a simpler functional form may suffice. This can be tested using Wald tests. It is particularly important to do this (in the fixed part of the model) given we are including cohort groups/generations as a stratum identifier, since in panel data these will be correlated with age, and, when age trajectories are allowed to vary, may produce intersectional differences in trajectories that could be better estimated as universal age trends. This will result in the stratum-level slope variance being overestimated in Model 1 when only a linear term is included, and so the slope PCV being underestimated.
2. If using such a polynomial function of age in the fixed part of the model, we may want to additionally allow the quadratic term to vary by strata and individual – this would allow not just the average trend to vary quadratically, but also allow different strata to have different quadratic curvatures. However, such a model would be notably more computationally intensive, estimating three further terms in the random part of the model at each level, and may require more data to be meaningfully estimated. Again, the fit of such models could be assessed against a simpler model, to judge whether that additional complexity is necessary. In many cases, though, such complexity will not provide any additional substantive insight, even when model fit statistics suggest it is the better-fitting model.
3. The example presented here and below uses a continuous outcome with residuals assumed to be independently and Normally distributed. We can relax the independence assumption by specifying, for example, autoregressive residuals. Similarly, it is certainly possible to fit equivalent models for non-continuous outcomes such as logistic regression for binary outcomes and Poisson regression for count outcomes. Indeed, these have been applied within the cross-sectional MAIHDA framework (Evans et al., 2024b; Mattsson et al., 2024; Persmark et al., 2020), and the extension is much the same in this longitudinal case.

These are innovative adaptations of already-existing multilevel modelling techniques, which can be applied in most standard statistical software packages. The use of random slopes for age is a novel extension of MAIHDA, though the potential for extending MAIHDA using random slopes/coefficients has previously been shown (Evans et al., 2023). The estimates will reveal the complexity of multiplicative stratum variability, and how that variability potentially varies across the life course.

5. Example: mental health trajectories in the UK

To illustrate the longitudinal intersectional MAIHDA approach, we consider inequalities in mental health trajectories in the UK. Mental health is particularly relevant here because it is dynamic in nature, and so a longitudinal approach helps to fully explore that dynamism. Risk factors for mental health accumulate through the life course (Lindstrom et al., 2014) and mental health episodes often have onsets and recoveries, and vary in longevity (Weich and Lewis, 1998). More recent studies have used the cross-sectional intersectional MAIHDA approach to identify intersectional inequalities in mental health, in the UK and elsewhere (Balloo et al., 2022; Evans and Erickson, 2019; Moreno-Agostino et al., 2023b). Meanwhile, a separate literature has explored average life course trajectories in mental health, again in a variety of international contexts. Mental health life course trajectories have been theorised to be U-shaped, and some empirical evidence supports this (Blanchflower and Oswald, 2008). However, others have argued that this is in part an artefact of the APC identification problem (Bell, 2014; Beller, 2022). Here, we consider how these trajectories might vary between different intersectional strata, in so doing bringing together these two important conceptual and empirical approaches to the study of mental health.

We use the UK Household Longitudinal Survey (UKHLS aka Understanding Society, Institute for Social and Economic Research, 2023). The dataset includes twelve yearly waves from 2009 to 2021, with a representative sample of UK households sampled, including a wide range of variables. The outcome of interest is measured using the General Health Questionnaire (GHQ, Goldberg and Williams, 1988) – a 12-item questionnaire where respondents answer questions with four Likert values, relating to their mental health, which are added together to form a single continuous scale (from 0 to 36, where higher values represent worse mental health). The measure has been shown to be highly correlated with clinical diagnoses of mental ill-health such as depression and anxiety. The questions that are used, and combined together, can be found in the online Appendix (Table A1).

The strata are defined by the following characteristics (see Table 1 for a full table of descriptive statistics) – the variables were chosen as there are strong evidence of differential mental health across each (e.g. Bell, 2014; Kurtze et al., 2013), but with limited evidence, at present, of intersectional effects between them:

1. Ethnicity – categorised as white, South Asian, Other Asian, Black, Mixed and Other. This is a slight disaggregation of the UK's Office for National Statistics five-category classification.
2. Generation – categorised by birth year as Silent Generation (born up to 1945), Baby Boomers (1946–1963), Generation X (1964–1979), Generation Y (1980–1994) and Generation Z (1995 onwards).
3. Education – categorised as No qualifications, up to GCSE or equivalent (age 16), up to A-level or equivalent (age 18), Higher Educated (e.g., university), Other Higher Educated, and Other.
4. Sex – categorised as Male and Female.

One of the challenges of MAIHDA lies in choosing an appropriate level of categorisation. With too few categories, estimates will not reveal potentially significant intersectional inequalities between subgroups that are grouped together. On the other hand, with too many categories, when combined with the other intersectional variables, groups will be too small to estimate intersectional equalities, especially for smaller (and often more disadvantaged groups). The above groupings have been chosen to attempt to balance these competing challenges, although we acknowledge that, in doing so, there will be some intersectional inequalities that our analysis will miss.

It is worth noting that we do not include other control variables that might typically be included in an analysis of mental health, such as partnership status, family circumstances and other socioeconomic measures. The purpose of the MAIHDA approach taken here is to uncover intersectional inequalities, and not what produces those inequalities. As such, controlling for other variables would be over-controlling, potentially removing important intersectional differences from the intersectional trajectories. Having said this, such variables could be included in the model where the interest is in more conditional intersectional differences.

Table 1
Variables used in this analysis.

Variable Name	Descriptive Statistics
GHQ (dependent variable)	Mean = 11.15, SD = 5.54, Range: 0-36
Age	Mean = 48.13, SD = 18.33, Range: 15-103
Ethnicity	White: 85%
	Mixed: 1.8%
	South Asian: 7.2%
	Other Asian 1.4%
	Black: 3.7%
	Other: 0.8%
Generation	Silent: 15.8%
	Boomer: 31.7%
	Gen X: 26.9%
	Gen Y: 20.3%
	Gen Z: 5.4%
Education	Degree: 27.6%
	Other Higher-level qual: 12.6%
	A-level and equivalent: 20.5%
	GCSE and equivalent: 19.3%
	Other: 9.0%
	No qualifications: 10.9%
Sex	Male: 44.2%
	Female: 55.8%

Note: We do not include sampling weights in this analysis since this is an illustrative example; however, weights could be used in such an analysis, potentially at both level 1 (longitudinal) and level 2 (cross-sectional).

This results in $6 \times 5 \times 6 \times 2 = 360$ categories, although in our data, five combinations of these are empty, leaving 355 strata. In our dataset there were a few instances (for sex, generation, and education) where individuals changed categories. In the case of education, the highest qualification achieved by the individual was used, as this most closely fits with the educational position construct that it is measuring. In the case of generation, these individuals were removed due to being unreliably measured. Whilst in some cases, changes in sex/gender might reveal important inequalities among transgender/genderfluid people, this was not possible here – the numbers where reported sex changed were small (only 100 observations), meaning that even if these were representative of gender transitions there are too few individuals to be able to uncover intersectional inequalities between them; these individuals were also removed from the sample. There are 399,473 observations (down from the full sample of 476,187 once missing values were removed), of 73,493 individuals with at least one wave of measurement. Because our strata variables are time-invariant, we can use the strictly hierarchical structure shown in Fig. 1. The strata were of varying sizes, with a median size of 123, but with a large range (from 1 to 16,682). However, this is not a problem per-se, since shrinkage accounts for the unreliability of smaller strata.

We follow the modelling strategy outlined in section 4. Initial models indicated that a cubic polynomial was needed for the age trend (by comparing to simpler models with the AIC), corroborating Bell (2014). Only the linear age component was allowed to vary at higher levels. The models were built up gradually to confirm that the intercept and slope variance at all three levels improved the fit of the model (again using the AIC). We present here the two main models (other models can be found in the online Appendix Table A2):

1. A model similar to equation (1), with a cubic polynomial for age, and the linear term allowed to vary at the stratum (level-3) and the individual (level-2) levels.
2. As above, but with the addition of main effects of the strata-defining characteristics, and interactions between those strata-defining characteristics and (linear) age (similar to equation (6)).

Model 1 shows the extent of stratum-level variation both in mean levels of GHQ, and in the age trajectory. Model 2 then shows the extent to which these are explained by additive main effects and interactions with the linear age trend. Models 1 and 2 are shown in Table 2. All models were fitted using the lme4 package in R (Bates et al., 2015), and code to reproduce it can be found in the online Appendix.

We can compare the variances at the stratum level between models 1 and 2 – however this is more complex than in a cross-sectional intersectional MAIHDA approach, because the variances vary as a function of age. It is informative to approach this in several ways. First, the model will calculate, separately, the stratum-level variance of the intercepts and slopes, and we can calculate intercept and slope PCVs (Equation (9)) to see how the addition of the main effects and age interactions explains the stratum-level variance. In this case, the main effects explain about 80% of the intercept variance and 42% of the slope variance (see Table 2). In other words, the majority of stratum-level differences in mental health, in terms of the baseline level for mean-aged people, is explained by the strata variables' additive main effects and age interactions – approximately 20% of the intercept variance, remains unaccounted for and so must be explained by multiplicative intersectional effects. A much larger proportion (over 50%) of the slope variance remains once interactions with age have been accounted for.

Alternatively, we can plot the stratum-level variances (along with the level-1 and level-2 variances, which are the same in both models – see equations (3), (4) and (8)) as a function of age. Fig. 2 shows that the stratum-level variance is highest for older people – that is, there are stronger intersectional inequalities among older groups than younger. When main effects are included in the model, these are significantly

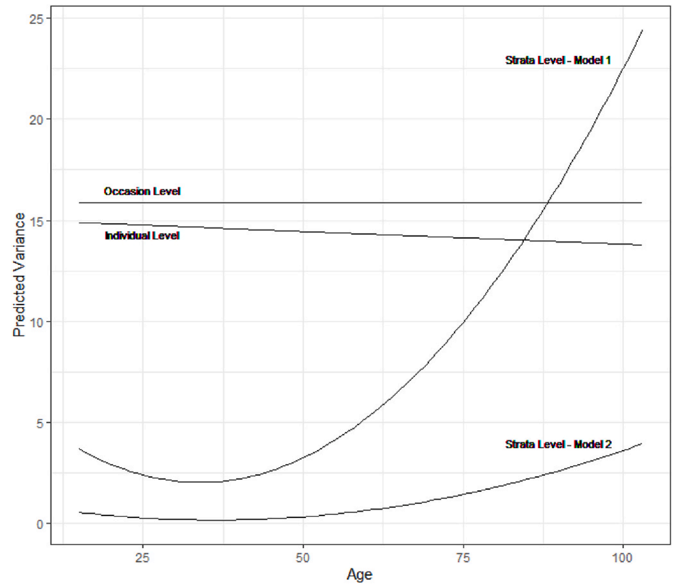

Fig. 2. Variance function estimates for Models 1 and 2.

Table 2
Longitudinal MAIHDA multilevel regression coefficient estimates, for models 1 and 2.

	Model 1		Model 2			
	Estimates	SE	Estimates	SE	Estimates	SE
Intercept	11.965***	0.088	8.869***	0.330		
Age (mean-centred)	−0.006	0.004	0.034	0.017		
Age^2	−0.002***	0.0001	−0.0006*	0.0002		
Age^3	0.00005***	0.000	0.00002***	0.000		
			Main effects		**Age interactions**	
Mixed Ethnicity (ref: white)			0.532**	0.195	−0.001	0.010
South Asian Ethnicity			−0.089	0.145	0.021**	0.008
Other Asian Ethnicity			−0.512*	0.202	0.014	0.011
Black Ethnicity			−0.821***	0.156	−0.0001	0.008
Other Ethnicity			0.335	0.213	0.0001	0.012
Baby Boomer (ref: Silent Gen)			2.273***	0.305	−0.079***	0.014
Gen X			1.662***	0.323	0.003	0.018
Gen Y			2.912***	0.355	0.038	0.023
Gen Z			7.610***	0.611	0.181***	0.032
Other Higher Ed (ref: Higher Ed)			0.450**	0.173	0.005	0.009
A-level			0.799***	0.167	0.003	0.009
GCSE			0.859***	0.168	0.006	0.009
Other			0.881***	0.182	0.003	0.010
No qualifications			1.827***	0.182	0.002	0.010
Female			0.943***	0.105	−0.018**	0.006
Random Effects						
Level-3 intercept variance	1.433		0.294			
Level-3 age-slope variance	0.002		0.0009			
Level-3 intercept-slope covariance	0.003		0.008			
Level-2 intercept variance	14.495		14.227			
Level-2 age-slope variance	0.000002		0.000003			
Level-2 intercept-slope covariance	−0.006		−0.006			
Level-1 variance	15.904		15.952			
Slope VPC: L3/(L2+L3)	99.8%		99.7%			
Intercept VPC: L3/(L2+L3)	9.0%		2.0%			
Slope PCV			42.4%			
Intercept PCV			79.5%			
N strata	355		355			
N individuals	75493		75493			
N observations	399473		399473			
AIC	2358405		2358234			
Deviance (−2×logliklihood)	2358383		2358152			

* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

reduced, but with the remaining multiplicative variance again being greatest among older people. It is also notable to compare this to the variances at level 2 and 1. The level-2 variance can be interpreted as differences between individuals within the same strata – this is significantly greater than the between-strata variance, and seems to reduce slightly with age – that is, older people see greater inequalities between strata, but more similarity within strata, than younger people. The level-1 variance can be interpreted as the extent of variability within individuals – that is, how volatile an individual's mental health is over the life course around their overall individual-specific smooth age trend. This is assumed to be constant across individuals by the model, and appears to be approximately the same order of magnitude as the between-individual, within-strata variance. This is important to note, since it is a reminder that, whilst there are important between-strata intersectional inequalities, the discriminatory accuracy of those strata remains low, with much greater variation within strata, and also greater volatility between occasions for a given individual.

In Table 2, we see all variables have significant main effects in Model 2. Worse mental health (high GHQ scores) is reported by individuals of mixed ethnicity, in more recent generations, with low education, and female. There are few significant age interactions effects, with the most notable being with generation (i.e., an age-by-cohort interaction); this is plotted in Fig. 3. Whilst most generations experience a worsening of mental health with age, Generation-Z individuals have a much steeper worsening of mental health as they age, compared to Generation-Y individuals of the same age. Baby Boomers appear to be unique in experiencing an improvement in their mental health. Model 2 finds that the best-fitting estimates involve these interactions, rather than a curve made entirely from a universal cubic age effect. This suggests that this improvement is in part a generation-specific phenomenon, that we would not expect more recently born generations to follow when they reach the Baby Boomers' age. However, we would advise against using such a plot to make predictions out of sample — for instance to imply either that baby boomers will continue to improve their mental health, or that other generations might experience a similar improvement at that age. Such distinctions made by the model are based only on the parts of the life course where the generations overlap, and may not be hugely reliable. Although the overlap is significant when comparing Gen Y and Gen Z, it is less significant when comparing Gen X and Baby Boomers. The differences may also be in part driven by period effects, meaning we would not necessarily expect the trajectories to continue that way in the future. However, whether driven by period effects, generational differences, or more universal age trajectories, the improving mental health of Baby Boomers, and the steeply worsening mental health of Generation Z, is notable in comparison to the trajectories of other generations.

So far, the analysis has focussed on broad findings across the sample; but it is equally informative to consider how particular intersectional strata differ from one another – indeed this is often the primary purpose of an intersectional analysis such as this. Each intersection has a

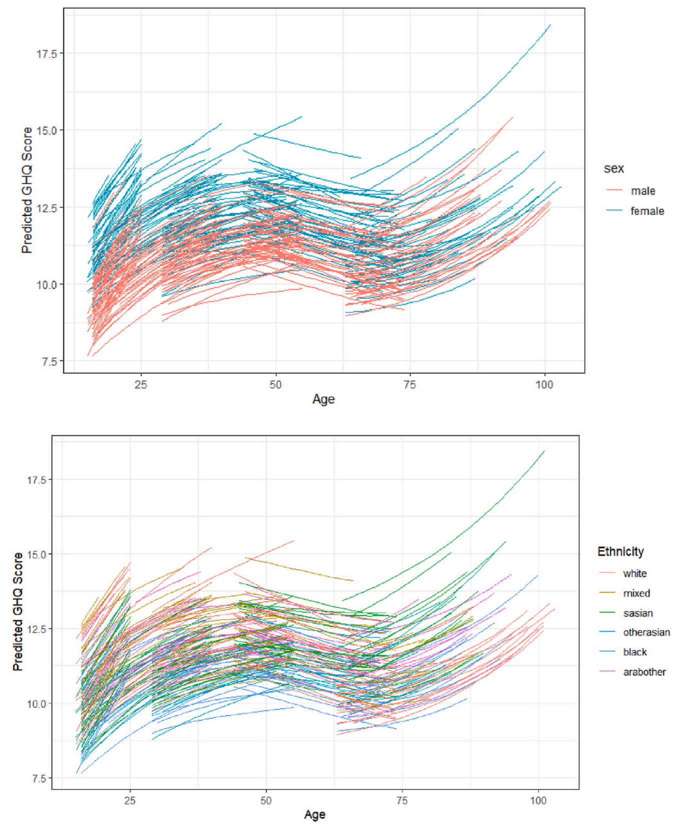

Fig. 4. Estimated GHQ age trajectories for each intersectional strata, estimated from Model 2. Strata are coloured by sex and ethnicity. Graphs coloured by education are in the online Appendix (Fig. A1).

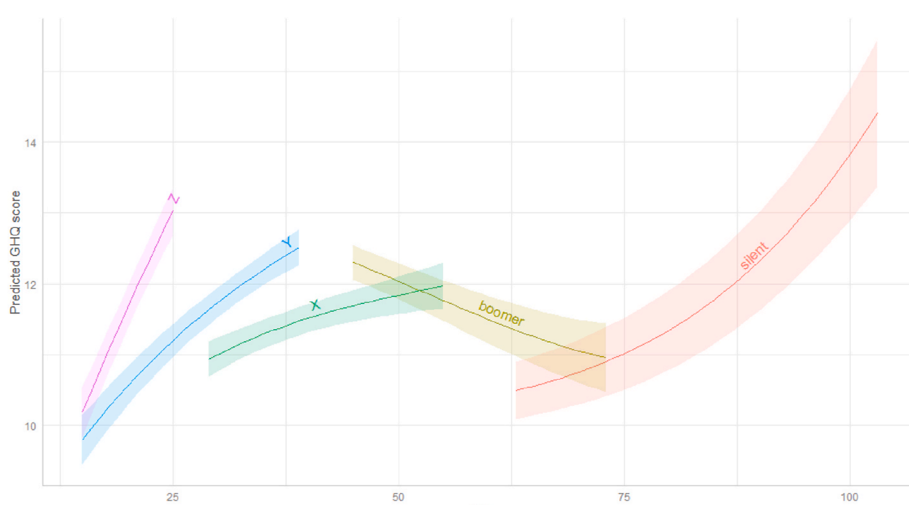

Fig. 3. Age-by-generation interaction plot from Model 2, showing the different trend experienced by baby boomers in the sample, all other variables not plotted are held constant at zero (so these are predictions for the reference category for other variables).

different mean and a different age trajectory, and these can be plotted, for instance, as in Fig. 4, which is coloured by sex and then ethnicity (see Appendix for a graph coloured by education). The sex divide can be clearly seen, with consistently lower (better) reported mental health scores among male strata compared to female strata. Educational inequalities are similarly clear (see online Appendix Fig. A1). Ethnicity appears more generationally patterned. Some white strata in Gen-Z appear to have worse mental health than other Gen-Z strata, whilst white strata in the Silent generation appear among the most mentally healthy. Black strata appear to have among the best (lowest) reported mental health across all generations.

We can also clearly see generational differences, mirroring the patterns in Fig. 3, since each generation is only measured for a certain age range in the sample – Generation Y and Z strata are on the left-hand side of the graph, whilst the Silent Generation strata are found on the right of the graph. Beyond that, it is somewhat difficult to get a detailed idea of what is happening in the graph (labelling each line would make the graph unreadable). Instead, we have created an interactive graph, which allows the reader to explore the differences between strata trajectories in full; it can be accessed here: https://rpubs.com/andrewjdbell/1182871. This allows readers to identify particular strata on the graph, and link them to equivalent strata in different generations. A few of these have been highlighted in Fig. 5. With lower GHQ (better mental health), we can see Black men with degrees (panel A) and Black women with degrees (panel B) – it is notable that in the younger generations, Black men report better mental health on average than Black women, but this appears to reverse for older generations. Otherwise, these generations conform to the overall patterns fairly consistently. Panels C and D highlight intersections with worse mental health – and the different generational patterns are notable here. White women with no qualifications have among the worst mental health for all generations except for the Silent generation – this may indicate changing intersectional inequalities with generations, but may also be due to the expansion of educational opportunities for women (Broeke and Hamed, 2008), resulting in a broader range of people being found in the low-educated Silent generation group. Among Black women with no qualifications, we see generally more moderate mental health scores – again, this could be in part a selection effect of Black women continuing to be excluded from educational opportunities in comparison to white women (Mirza and Warwick, 2022), meaning the low-educated groups are more diverse. In this way, we can identify sex-education-ethnicity combinations with particularly disadvantaged strata, and highlight intersectional generational relative disadvantage. In this case, there are limited examples of such generational jumps – sex-education-ethnicity combinations for the most part overlap with each other, suggesting minimal cohort-related multiplicativity, and life course effects that conform, approximately, to a cubic polynomial and the age-generation interactions highlighted above. It should be noted that the graphs here do not reveal the uncertainty of the estimates, which for small intersectional strata will be large. However, thanks to shrinkage, smaller strata are likely to be estimated conservatively, close to the mean expected given their combination of additive effects.

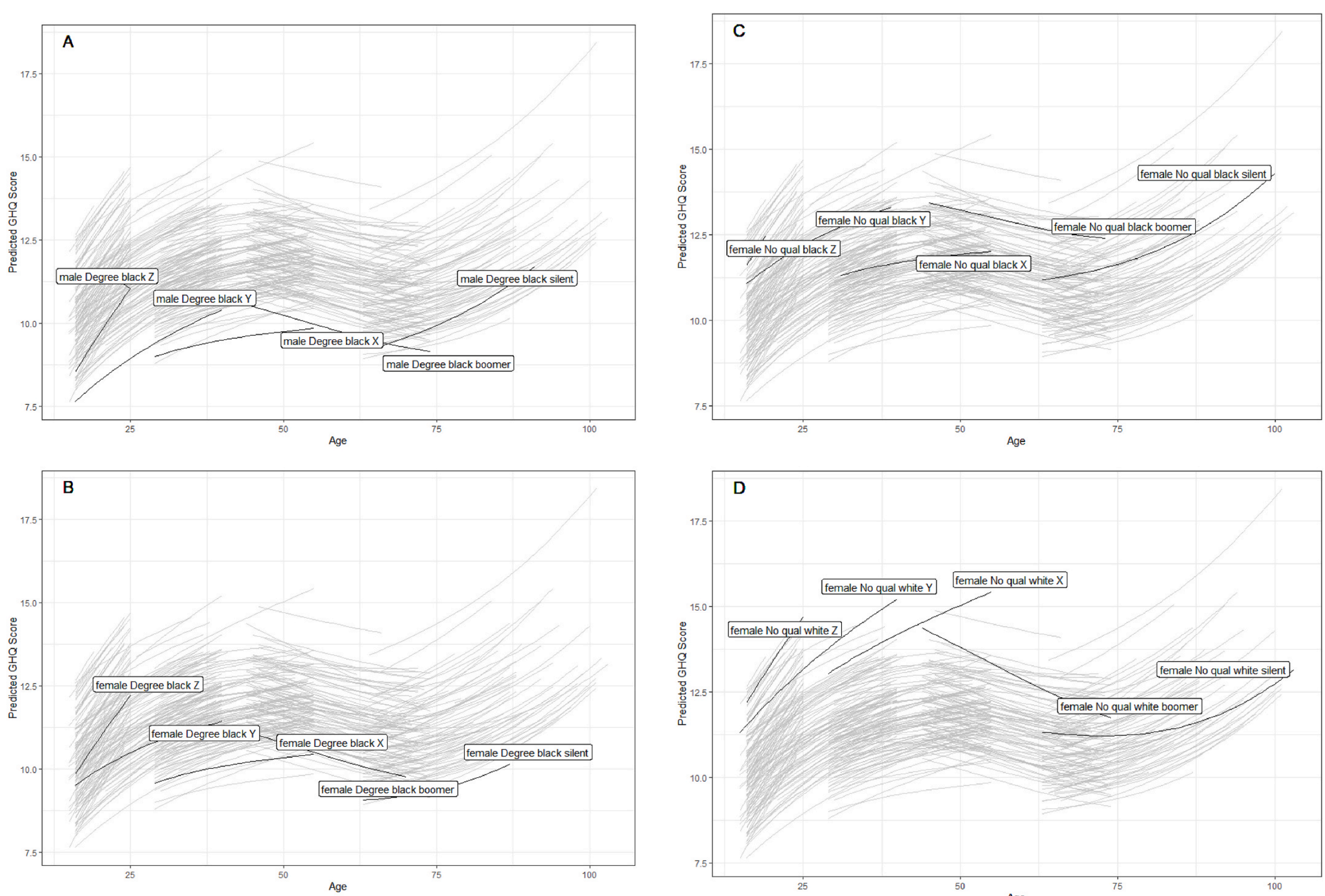

Fig. 5. Estimated GHQ age trajectories for each intersectional strata, estimated from Model 2. Some example sex-education-ethnicity combinations highlighted. Panel A: Degree-educated Black men; Panel B: Degree-educated Black women; Panel C: Black women with no qualifications; Panel D: white women with no qualifications.

Overall, this example applications reveals:

- Between-strata variability accounts for a small but significant proportion of mental health inequalities. Among young people this is mostly accounted for by additive effects, but among older people a greater proportion is a result of multiplicative intersectional inequalities. This could be a result of (dis)advantages accumulating over the life course (O'Rand, 1996).
- The relatively small stratum-level differences are generally to be expected, but are an important reminder to avoid the "Tyranny of Averages" (Merlo et al., 2017), with significant heterogeneity within intersectional strata.
- Baby Boomers and Generation Z appear to have a categorically different mental health trajectory to other birth cohorts (at least in the time-period under study). Baby boomers have mental health that appears to improve as they age compared to other generations that have worsening mental health. Generation Z has mental health trajectories that worsen at a much faster rate as they age than Generation Y at the same age.
- There are clear additive inequalities in mental health in ethnicity, generation, education level, and sex. Ethnicity differences appear to intersect with generation, with white, Gen-Z strata among the most mentally unhealthy, and white, Silent-generation groups among the most mentally healthy.
- There are some specific intersectional groups that operate in ways that are slightly different to what would be expected from their mental health – these complexities can be explored but require further research to understand their meaning.

6. Conclusions

This paper has presented an extension to the intersectional MAIHDA approach, for analysing longitudinal data, by thinking about how *trajectories* can vary across strata. The approach is easy to implement in most standard statistical software packages that can fit random slopes multilevel models. The method has the potential to be extremely valuable to researchers hoping to understand intersectional disadvantage in longitudinal data, as well as those considering other, non-intersectional interactions between categories over time.

The approach is also highly flexible, and could be applied to different types of longitudinal data with some minor adjustments. The example used here involved panels with individuals nested in non-changing strata, but a cross-classified model (Hox et al., 2017, chapter 9), would allow for the possibility of non-changing, fluid intersectional identities/strata, as shown in Fig. 6, allowing individuals to belong to a different stratum in each measurement occasion. Such an approach would be partly informed by anti-categorical intersectional scholarship, which highlights the fluidity of intersectional groups (McCall, 2005). The algebraic specification of the models would similar to the strictly hierarchical case demonstrated here, and in R/lme4, the code to do so would be the same too. Such an approach could in theory be further extended with the addition of other cross-classified levels of analysis (such as household and neighbourhood) – past work has considered this with cross-sectional data (Holman et al., 2022). Whilst the focus of this paper has been panel data, a version of the method could be used with birth-cohort studies (although the latter would not have variation

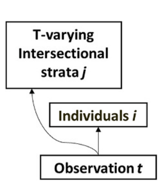

Fig. 6. Longitudinal MAIHDA structure, where intersectional strata are changeable for individuals.

between generations to explore). If using repeated cross-sectional data, a model with a similar logic could be used (with individuals nested in strata and, potentially, cross-classified with survey waves). A version of this model could also be adapted for outcomes suitable to a survival analysis, for example by fitting a multilevel Cox regression.

The example here highlights the challenge of potentially competing explanations between age and cohort trajectories. The problem is particularly tricky where panels are shorter, and therefore the overlap of generational age trajectories is minimal. Longer panels, that allow generations to have significantly overlapping age ranges, will help to tell a more convincing story. But even in such cases, we cannot be sure that the results are driven by age/cohort rather than period trends, because of the identification problem. Following Fosse and Winship (2023), we argue that such patterns are interesting, highlighting important differences between generational groups, regardless of the temporal processes driving them.

With relatively complex models such as these, model convergence can be an issue, particularly where there are relatively few higher-level groups and/or relatively few individuals within those groups. There are a few things that can help with this: centring and rescaling of the age variable, allowing for non-constant variance at level 1, or using Bayesian estimation methods. However, such non-convergence can also be a sign that the model is attempting to do too much – perhaps attempting to find differences between very small intersectional strata, for instance. Some caution in the setup of the model – in choosing the intersecting variables and so the number and size of the strata – is warranted here (Evans et al., 2024b).

Finally, it is important throughout the modelling approach to consider the theoretical underpinnings of the model, with reference to the intersectional theory that inspires it. The model is inherently exploratory unless combined with strong theory about intersectional strata, and so should generally be used as a starting point to understand intersectional disadvantage, not as a tool for atheoretically explaining those inequalities or prescribing solutions to them. Mixed methods research with in-depth qualitative investigation of the strata is likely the gold standard approach, here.

Having said that, the approach presents a valuable way of exploring and describing not just the intersectional inequalities that exist at a particular point in time, but also the inequalities in the trajectories that individuals follow. It does so in a way which highlights key aspects of an intersectional life course perspective. Following Ferrer et al. (2017), the approach allows consideration of how different individuals are affected by different life stages, or have different trajectories, and the inequalities that those trajectories produce. It allows consideration of the structural forces that influence individuals' lives at different times, and how these multiple identities combine to produce difference and inequalities in temporally varying ways. When combined with critical theory and qualitative methods, there is scope for such differences to be explained by considering the agency of individuals within their intersectional identities, and the structural systems of domination and resistance formed through them.

Ethics statement

The empirical research presented in this paper involves only secondary research data that has been robustly anonymised. As such, no further ethics approval is required.

CRediT authorship contribution statement

Andrew Bell: Writing – review & editing, Writing – original draft, Visualization, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Clare Evans:** Writing – review & editing, Writing – original draft, Methodology. **Dan Holman:** Writing – review & editing, Writing – original draft, Conceptualization. **George Leckie:** Writing – review & editing, Methodology.

Data availability

The data can be accessed through the UK Data Service. The code to run the analysis is provided in an online appendix.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2024.116955.

References

Alvarez, C.H., Calasanti, A., Evans, C.R., Ard, K., 2022. Intersectional inequalities in industrial air toxics exposure in the United States. Health Place 77, 102886.
Alvarez, C.H., Evans, C.R., 2021. Intersectional environmental justice and population health inequalities: a novel approach. Soc. Sci. Med. 269, 113559.
Balloo, K., Hosein, A., Byrom, N., Essau, C.A., 2022. Differences in mental health inequalities based on university attendance: intersectional multilevel analyses of individual heterogeneity and discriminatory accuracy. SSM - Population Health 19, 101149.
Bates, D.M., Mächler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Software 67 (1), 1–48.
Beccia, A.L., Baek, J., Austin, S.B., Jesdale, W.M., Lapane, K.L., 2021. Eating-related pathology at the intersection of gender identity and expression, sexual orientation, and weight status: an intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA) of the Growing up Today Study cohorts. Soc. Sci. Med. 281, 114092.
Bell, A., 2014. Life-course and cohort trajectories of mental health in the UK, 1991-2008: a multilevel age-period-cohort analysis. Soc. Sci. Med. 120, 21–30.
Bell, A., 2020. Age-Period-Cohort analysis: a review of what we should and shouldn't do. Ann. Hum. Biol. 47 (2), 208–217.
Bell, A., Holman, D., Jones, K., 2019. Using shrinkage in multilevel models to understand intersectionality: a simulation study and a guide for best practice. Methodology 15 (2), 88–96.
Beller, J., 2022. Age-period-cohort analysis of depression trends: are depressive symptoms increasing across generations in Germany? Eur. J. Ageing 19 (4), 1493–1505.
Ben-Shlomo, Y., Kuh, D., 2002. A life course approach to chronic disease epidemiology: conceptual models, empirical challenges and interdisciplinary perspectives. Int. J. Epidemiol. 31 (2), 285–293.
Blanchflower, D.G., Oswald, A.J., 2008. Is well-being U-shaped over the life cycle? Soc. Sci. Med. 66 (8), 1733–1749.
Broeke, S., Hamed, J., 2008. Gender gaps in higher education participation. Department for Innovation, Universities and Skills Research Report 8 (14). https://dera.ioe.ac.uk/id/eprint/8717/.
Brotman, S., Ferrer, I., Koehn, S., 2020. Situating the life story narratives of aging immigrants within a structural context: the intersectional life course perspective as research praxis. Qual. Res. 20 (4), 465–484.
Bullen, N., Jones, K., Duncan, C., 1997. Modelling complexity: analysing between-individual and between-place variation: a multilevel tutorial. Environ. Plann. 29 (4), 585–609.
Crenshaw, K., 1989. Demarginalizing the intersection of race and sex: a Black feminist critique of antidiscrimination doctrine, feminist theory and antiracist politics. Univ. Chicago Leg Forum 1989 (1), 139–167.
Crenshaw, K., 1991. Mapping the Margins: intersectionality, identity politics, and violence against women of color. Stanford Law Rev. 43 (6), 1241.
Dressel, P., Minkler, M., Yen, I., 1997. Gender, race, class, and aging: advances and opportunities. International Journal of Social Determinants of Health and Health Services 27 (4), 579–600.
Evans, C.R., Borrell, L., Bell, A., Holman, D., Subramanian, S.V., Leckie, G., 2024a. Clarifications on the intersectional MAIHDA approach: A conceptual guide and response to Wilkes and Karimi. Social Science & Medicine 350, 116898.
Evans, C.R., Erickson, N., 2019. Intersectionality and depression in adolescence and early adulthood: a MAIHDA analysis of the national longitudinal study of adolescent to adult health, 1995–2008. Soc. Sci. Med. 220, 1–11.
Evans, C.R., Leckie, G., Subramanian, S., Bell, A., Merlo, J., 2024b. A tutorial for conducting intersectional multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA). SSM - Population Health 26, 101664.
Evans, C.R., Nieves, C.I., Erickson, N., Borrell, L.N., 2023. Intersectional inequities in the birthweight gap between twin and singleton births: a random effects MAIHDA analysis of 2012–2018 New York City birth data. Soc. Sci. Med. 331, 116063.
Evans, C.R., Williams, D.R., Onnela, J.-P., Subramanian, S.V., 2018. A multilevel approach to modeling health inequalities at the intersection of multiple social identities. Soc. Sci. Med. 203, 64–73.
Ferrer, I., Grenier, A., Brotman, S., Koehn, S., 2017. Understanding the experiences of racialized older people through an intersectional life-course perspective. J. Aging Stud. 41, 10–17.
Fosse, E., Winship, C., 2023. The anatomy of cohort analysis: decomposing comparative cohort careers. Socio. Methodol. 53 (2), 217–268.
Goldberg, D., Williams, P., 1988. A User's Guide to the General Health Questionnaire. NFER-NELSON.
Hill Collins, Patricia, 2008. Black Feminist Thought: Knowledge, Consciousness, and the Politics of Empowerment. Routledge.
Hockey, J., James, A., 2017. Social Identities across the Life-Course. Bloomsbury.
Holman, D., Bell, A., Green, M., Salway, S., 2022. Neighbourhood deprivation and intersectional inequalities in biomarkers of healthy ageing in England. Health Place 77, 102871. https://doi.org/10.1016/J.HEALTHPLACE.2022.102871.
Holman, D., Salway, S., Bell, A., 2020. Mapping intersectional inequalities in biomarkers of healthy ageing and chronic disease in older English adults. Sci. Rep. 10 (1), 1–12.
Holman, D., Walker, A., 2021. Understanding unequal ageing: towards a synthesis of intersectionality and life-course analyses. Eur. J. Ageing 18 (2), 239–255.
Hox, J.J., Moerbeek, M., van de Schoot, R., 2017. Multilevel Analysis: Techniques and Applications, second ed. Routledge.
Institute for Social and Economic Research, 2023. Understanding Society: Waves 1-13, 2009-2022. UK Data Service.
Keller, L., Lüdtke, O., Preckel, F., Brunner, M., 2023. Educational inequalities at the intersection of multiple social categories: an introduction and systematic review of the multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA) approach. Educ. Psychol. Rev. 35 (1), 1–37.
Kuh, D., Ben-Shlomo, Y., Lynch, J., Hallqvist, J., Power, C., 2003. Life course epidemiology. Journal of Epidemiology and Community Health 57 (10), 778.
Kurtze, N., Eikemo, T.A., Kamphuis, C.B.M., 2013. Educational inequalities in general and mental health: differential contribution of physical activity, smoking, alcohol consumption and diet. Eur. J. Publ. Health 23 (2), 223–229.
Lindstrom, M., Fridh, M., Rosvall, M., 2014. Economic stress in childhood and adulthood, and poor psychological health: three life course hypotheses. Psychiatr. Res. 215, 386–393.
Mahendran, M., Lizotte, D., Bauer, G.R., 2022. Describing intersectional health outcomes: an evaluation of data analysis methods. Epidemiology 33 (3), 395–405.
Mattsson, H., Gustafsson, J., Prada, S., Jaramillo-Otoya, L., Leckie, G., Merlo, J., Rodriguez-Lopez, M., 2024. Mapping socio-geographical disparities in the occurrence of teenage maternity in Colombia using multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA). Int. J. Equity Health 23 (1), 1–18.
McCall, L., 2005. The complexity of intersectionality. Signs 30 (3), 1771–1800.
Merlo, J., 2011. Contextual influences on the individual life course: building a research framework for social epidemiology. Psychosoc. Interv. 20 (1), 109–118. https://doi.org/10.5093/IN2011V20N1A9.
Merlo, J., Mulinari, S., Wemrell, M., Subramanian, S.V., Hedblad, B., 2017. The tyranny of the averages and the indiscriminate use of risk factors in public health: the case of coronary heart disease. SSM - Population Health 3, 684–698.
Mirza, H.S., Warwick, R., 2022. Race and Ethnicity. Institute for Fiscal Studies Deaton Review of Inequalities. https://ifs.org.uk/publications/race-and-ethnicity.
Moen, P., Miller, M., 2022. Inequalities in work and the intersectional life course. In: Nico, M., Pollock, G. (Eds.), The Routledge Handbook of Contemporary Inequalities and the Life Course. Routledge, pp. 349–361.
Moreno-Agostino, D., Fisher, H.L., Hatch, S.L., Morgan, C., Ploubidis, G.B., Das-Munshi, J., 2023a. Generational, sex, and socioeconomic inequalities in mental and social wellbeing during the COVID-19 pandemic: prospective longitudinal observational study of five UK cohorts. Psychol. Med. 53 (13), 6403–6414.
Moreno-Agostino, D., Woodhead, C., Ploubidis, G.B., Das-Munshi, J., 2023b. A quantitative approach to the intersectional study of mental health inequalities during the COVID-19 pandemic in UK young adults. Soc. Psychiatr. Psychiatr. Epidemiol. https://doi.org/10.1007/s00127-023-02424-0.
O'Rand, A.M., 1996. The precious and the precocious: understanding cumulative disadvantage and cumulative advantage over the life course. Gerontol. 36 (2), 230–238.
Persmark, A., Wemrell, M., Evans, C.R., Subramanian, S.V., Leckie, G., Merlo, J., 2020. Intersectional inequalities and the U.S. opioid crisis: challenging dominant narratives and revealing heterogeneities. Crit. Publ. Health 30 (4), 398–414.
Prior, L., Evans, C., Merlo, J., Leckie, G., 2022. Sociodemographic inequalities in student achievement: An intersectional multilevel analysis of individual heterogeneity and discriminatory accuracy (MAIHDA). ArXiv. https://arxiv.org/abs/2211.06321.
Rudolph, C.W., Zacher, H., 2022. Generations, we hardly knew ye: an obituary. Group Organ. Manag. 47 (5), 928–935.
Silva, T., Evans, C.R., 2020. Sexual identification in the United States at the intersections of gender, race/ethnicity, immigration, and education. Sex. Roles 83, 722–738.
Weich, S., Lewis, G., 1998. Material standard of living, social class, and the prevalence of the common mental disorders in Great Britain. Journal of Epidemiology and Community Health 52 (1), 8–14.
Zubizarreta, D., Beccia, A.L., Trinh, M.H., Reynolds, C.A., Reisner, S.L., Charlton, B.M., 2022. Human papillomavirus vaccination disparities among U.S. college students: an intersectional Multilevel Analysis of Individual Heterogeneity and Discriminatory Accuracy (MAIHDA). Soc. Sci. Med. 301, 114871.