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# Do We Become More Lonely With Age? A Coordinated Data Analysis of Nine Longitudinal Studies

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**Abstract**

Loneliness is a pervasive experience with adverse impacts on health and well-being. Despite its significance, notable gaps impede a full understanding of how loneliness changes across the adult life span and what factors influence these changes. To address this, we conducted a coordinated data analysis of nine longitudinal studies encompassing 128,118 participants ages 13 to 103 from over 20 countries. Using harmonized variables and models, we examined loneliness trajectories and predictors. Analyses revealed that loneliness follows a *U*-shaped curve, decreasing from young adulthood to midlife and increasing in older adulthood. These patterns were consistent across studies. Several baseline factors (i.e., sex, marital status, physical function, education) were linked to loneliness levels, but few moderated the loneliness trajectories. These findings highlight the dynamic nature of loneliness and underscore the need for targeted interventions to reduce social disparities throughout adulthood.

**Keywords**

loneliness, lifespan development, coordinated analysis

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Loneliness, the subjective feeling of a lack of meaningful social connections or a sense of belongingness, is a pervasive and distressing phenomenon affecting individuals across various age groups and populations (Cacioppo & Cacioppo, 2014). Given its high prevalence and adverse impacts on mental and physical health (Anderson & Thayer, 2018; Courtin & Knapp, 2017), understanding loneliness pathways throughout adulthood and contributing factors is crucial. Although loneliness research has rapidly grown and proliferated, a comprehensive understanding of developmental patterns and predictors of change is still lacking (Mund, Freuding, et al., 2020).

Some studies propose a *U*-shaped curve, with heightened levels in adolescence and older adulthood versus midlife (Lay-Yee et al., 2021; Nyqvist et al., 2016; Perlman, 1990). However, inconsistent patterns across age groups are also documented (Luhmann & Hawkley, 2016; Mund, Lüdtke, & Neyer, 2020). Furthermore, methodological limitations, including reliance on cross-sectional data and lack of standardized measurements, have hindered the generalizability and comparability of extant findings.

A meta-analysis of 75 longitudinal studies revealed decreasing loneliness from childhood to adolescence, stabilizing thereafter (Mund, Freuding, et al., 2020).

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However, significant heterogeneity in trajectories was found, highlighting the importance of examining predictors that contribute to individual differences in loneliness changes. Moreover, many of the studies included had relatively short follow-up periods and few measurement occasions, limiting the detection of nonlinear patterns or long-term trends.

The current preregistered study addresses gaps in understanding how loneliness changes across the life span using coordinated data analysis (CDA). We investigated and compared longitudinal patterns of loneliness across nine independent panel studies (the English Longitudinal Study of Aging [ELSA]; the German Socio-Economic Panel [GSOEP]; the Health and Retirement Study [HRS]; Household, Income, and Labour Dynamics in Australia [HILDA]; Longitudinal Internet Studies for Social Sciences [LISS]; Origins of Variance in the Oldest-Old: Octogenarian Twins [Octo-Twin]; the Swedish Adoption/Twin Study of Aging [SATSA]; the Survey of Health, Aging, and Retirement in Europe [SHARE]; and the Swiss Household Panel [SHP]). CDA is a form of integrative data analysis that synthesizes results from multiple heterogeneous data sources to draw conclusions about a common set of research questions (Graham et al., 2022; Hofer & Piccinin, 2009). It is a powerful approach for integrating existing life span data. Using this approach, investigators identify datasets that contain the minimum requisite data to address a given question (e.g., three longitudinal measurement occasions of loneliness). They then develop standardized procedures for harmonizing key variables, transforming them onto common metrics, and fitting identical statistical models. Although datasets are analyzed separately, they can vary on country, baseline year, instruments, and other study-level characteristics. This often efficiently provides comprehensive, generalizable answers to foundational life span research questions where replicability is imperative and emerges piecemeal from traditional meta-analysis.

This study employed CDA to address three interrelated research questions around age-related loneliness patterns and predictors. Specifically, we examined (a) how loneliness changes across adulthood and whether trajectories are linear versus nonlinear (*U*-shaped), (b) if baseline sociodemographic and health factors predict mean levels of loneliness, and (c) if these baseline variables moderate changes in loneliness over time. We focused our predictors on factors previously linked to loneliness, including social isolation, sex, baseline age, marital status, education, income, functional limitations, health behaviors, cognitive health, physical health, and mental health (Dahlberg et al., 2022; O'Súilleabháin et al., 2019; Soest et al., 2020). We hypothesized loneliness would remain relatively stable in midlife before increasing in older age. Additionally, we predicted individuals older at baseline, less educated, more socially isolated, lacking a partner, widowed, or physically limited would report higher loneliness levels on average. Such high-risk groups were also expected to experience more dramatic linear and nonlinear rises in loneliness over lengthy follow-ups. In addition, we predicted that women's loneliness levels would increase steadily, whereas men would show a *U*-shaped age trend, with decreasing loneliness until about age 70 and an increase thereafter.

## Statement of Relevance

Loneliness and social isolation are currently considered major threats to health and well-being in older adulthood. Thus, understanding who is at risk for persistent and increasing loneliness across the life span is imperative in order to mitigate downstream health impacts. Yet our knowledge of the developmental trends in loneliness is limited. The present research replicated trajectories of loneliness in nine large longitudinal studies ($N$ = 128,118) and found that loneliness follows a *U*-shaped curve, decreasing from young adulthood to midlife and increasing in older adulthood. Several baseline factors (i.e., sex, marital status, physical function, education) were linked to loneliness levels. Importantly, these patterns were consistent across studies, lending credence to the generalizability of our findings. This research highlights the dynamic nature of loneliness and underscore the need for targeted interventions aimed at reducing social disparities throughout adulthood and with sensitivity to life span patterns and change.

# Method

The present study was preregistered on the Open Science Framework (OSF; https://osf.io/67tfa/?view_only=9c3bc61fdf864c67ab30fcdf160c6280) with three longitudinal samples, which we later expanded to include six additional samples that met inclusion criteria. All code scripts, results, and supplementary material (from both the preliminary and final analyses) are publicly available at https://osf.io/67tfa/?view_only=9c3bc61fdf864c67ab30fcdf160c6280) and an R Shiny web application. Data used for the current study were full deidentified existing limited datasets from long-term longitudinal panel studies, and as such, the current work is not considered human subjects research and does not require approval by an institutional review board.

**Table 1.** Study Information

| Study | Country | N | Baseline year | MO | Interval[a] | Age range | Female | Loneliness scale |
|---|---|---|---|---|---|---|---|---|
| ELSA | England | 5,953 | 2004 | 7 | 2 | 23–90 | 56% | UCLA |
| GSOEP | Germany | 17,367 | 1990 | 20 | 1 | 17–93 | 52% | CES-D |
| HILDA | Australia | 25,821 | 2006 | 13 | 1 | 15–98 | 52% | CES-D |
| HRS | United States | 1,713 | 2008/10 | 5 | 2 | 25–92 | 61% | UCLA |
| LISS | Netherlands | 12,792 | 2009 | 12 | 1 | 15–100 | 54% | Rasch-type |
| Octo-Twin | Sweden | 606 | 1991 | 5 | 2 | 79–98 | 66% | CES-D |
| SATSA | Sweden | 1,852 | 1985 | 9 | 3 | 29–96 | 59% | CES-D |
| SHARE | European Union, Switzerland, Israel | 45,389 | 2004 | 4 | 2 | 24–103 | 56% | UCLA |
| SHP | Switzerland | 16,625 | 1999 | 14 | 1 | 13–96 | 53% | CES-D |

Note: MO = measurement occasion; ELSA = English Longitudinal Study of Aging; GSOEP = German Socio-Economic Panel; HRS = Health and Retirement Study; HILDA = Household, Income, and Labour Dynamics in Australia; LISS = Longitudinal Internet Studies for Social Sciences; Octo-Twin = Origins of Variance in the Oldest-Old: Octogenarian Twins; SATSA = Swedish Adoption/Twin Study of Aging; SHARE = Survey of Health, Aging, and Retirement in Europe; SHP = Swiss Household Panel; CES-D = Center for Epidemiologic Studies Depression Scale.
[a]Indicates years between measurement occasions.

The current study examined longitudinal loneliness trajectories across adulthood, comparing patterns across nine independent panel studies. We investigated a range of predictors of loneliness based on prior work (e.g., Soest et al., 2020) including social isolation, sex, baseline age, marital status, education, and functional limitations. These variables aimed to confirm and expand established risk factors. Notably, relevant studies by Mund, Freuding, et al. (2020) and Dahlberg et al. (2022) emerged after formulating our analysis plan. As such, we acknowledge that this study is building upon that work. We used coordinated data analysis with random-effects meta-analysis to evaluate and integrate the multistudy datasets (Graham et al., 2022; Hofer & Piccinin, 2009; Mroczek et al., 2021; Willroth et al., 2022). This approach enabled partially replicating and significantly expanding earlier findings of loneliness changes over extensive (up to 27 years) time frames (Mund, Freuding, et al., 2020). Specifically, employing coordinated analysis facilitated comparing the magnitude and direction of associations between key predictors and loneliness fluctuations across studies in addition to harmonizing models and measurement. Ultimately, coordinated analysis is an invaluable technique for synthesizing replicable, generalizable outcomes across existing life span data sources to advance the field (Graham et al., 2020; Hofer & Piccinin, 2009). By using coordinated analysis to answer these questions, we enhance the innovation of this work and the generalizability of our findings.

## *Studies and participants*

See Table 1 for a summary of the studies used in the analysis.

ELSA is a longitudinal panel study of adults who are over 50 years of age living in England (Steptoe, Breeze, et al., 2013). The study began in 2002, and additional waves of data were collected every 2 years until 2016 via computer-assisted interviews and self-report questionnaires. Data can be requested directly through the ELSA website. For the current project, baseline was defined as Wave 2 (2004), as this was the first occasion that included the UCLA Loneliness Scale. This project used seven total measurement occasions spanning 12 years. A total of 5,953 (56% female, 23–90 years at baseline) participants completed at least one assessment of loneliness.

GSOEP is a longitudinal household panel study of individuals from approximately 11,000 households in Germany ages 17 and older (Goebel et al., 2019). The study began in 1984, with annual assessments to the present. A total of 17,367 (52% female; 17–93 years old at baseline) participants completed at least one assessment of loneliness.

HRS is a longitudinal, nationally representative panel study of individuals in the United States ages 51 and older (Sonnega et al., 2014). The study was initiated in 1992, with measurement occasions every 2 years to the present. The first assessment of loneliness occurred in 2008 for half of the sample and 2010 for the remainder of participants, which were combined into a single sample. A total of 1,713 (61% female; 25–92 years at baseline) participants completed at least one assessment of loneliness.

HILDA is a longitudinal household panel study of individuals in Australia ages 15 and older (Wilkins et al., 2015). Baseline assessments occurred in 2001 and measurement occasions took place annually to the present. A total of 25,821 (52% female; 15-98 years at baseline) participants completed at least one assessment of loneliness.

LISS is a panel survey that is administered online by the Centerdata research institute in the Netherlands. The sample consists of respondents from approximately 5,000 households in the Netherlands, totaling 7,500 participants (ages 16+). Baseline measures occurred in 2007, with ongoing annual measurement assessments. A total of 12,792 (54% female; 15–100 years at baseline) participants completed at least one assessment of loneliness.

Octo-Twin is a sample from the Swedish population-based twin registry. At study initiation, twin pairs were enrolled if they were born in 1913 or earlier and both twins consented to participation. A total of 351 twin pairs were enrolled (*N* = 702) in 1991, and new waves of data collection occurred every 2 years until 2002 (when the majority of the sample was deceased), resulting in a total of five measurement occasions possible for analysis (McClearn et al., 1997). A total of 606 (66% female; 79–98 years at baseline) participants completed at least one assessment of loneliness.

SATSA is a longitudinal study aimed at investigating correlates of genetics in adulthood. The original sample, first collected in 1984, consisted of pairs of twins reared apart, matched with control pairs of twins reared together (total *N* = 3,838). New waves of data collection occurred approximately every 3 years, for a total of nine waves of data available for analysis (Pedersen et al., 1991). A total of 1,852 (59% female; 29–96 years at baseline) participants completed at least one assessment of loneliness.

SHARE is a panel study of individuals ages 50 and over living in 26 countries of the European Union, Switzerland, and Israel (Börsch-Supan et al., 2013). Assessment of baseline data occurred in 2004, and ongoing measurement occasions took place every 2 years. A total of 45,389 (56% female; 24–103 years at baseline) participants completed at least one assessment of loneliness.

SHP is a longitudinal study of individuals in Switzerland ages 13 and older (Tillmann et al., 2016). Baseline data were assessed in 1999, with subsequent assessments occurring annually (ongoing). A total of 16,625 (53% female; 13–96 years at baseline) participants completed at least one assessment of loneliness and were included in the current analysis.

## Measures

Loneliness was measured in ELSA, HRS, and SHARE using three items from the UCLA Loneliness Scale (Hughes et al., 2004). At each wave, participants rated how often they lacked companionship, felt left out, and felt isolated from others. Each item was rated on a 4-point scale (0 = *rarely or none of the time*; 1 = *some or a little of the time*; 2 = *occasionally or a moderate amount of time*; 3 = *most or all of the time*). A total loneliness score was calculated within each wave by computing the mean of the three items. The LISS study used the Rasch-Type Loneliness Scale (De Jong-Gierveld & Kamphuls, 1985). All other studies used the *Center for Epidemiologic Studies Depression Scale* single-item measure, rating loneliness frequency (Brantley et al., 2000). We opted to use the single-item measure of loneliness in GSOEP due to inconsistent sampling across waves for the UCLA scale. Response options varied between studies. Specifically, LISS used a 3-point response option. We used three items from the six-item Rasch-Type Loneliness Scale for LISS. Three of the items directly assess the emotional component of loneliness ("I miss having people around me," "I have a sense of emptiness around me," and "I often feel deserted") and three of the items are more related to the relationship component of loneliness ("I know a lot of people that I can fully rely on," "There are enough people I can count on in case of a misfortune," and "There are enough people to whom I feel closely connected"). Because we were interested in the emotional components of loneliness in the present study, not the relational ones, we opted to use only those items for comparability to assessments in other studies. HILDA used a 7-point scale, and SHP used an 11-point scale. Loneliness scores were transformed to percentage of maximum possible scores for optimal comparability across measurement occasions and studies. Across all studies and measurement occasions, higher scores reflected greater loneliness.

***Predictors.*** Predictors were selected on the basis of prior work with the goal of parsing loneliness variance and modeling trajectories adjusted for health and well-being factors (O'Súilleabháin et al., 2019; Steptoe, Shankar, et al., 2013). A number of studies suggest that these factors either are directly linked to loneliness or are implicated in health and mortality (Dahlberg et al., 2022; O'Súilleabháin et al., 2019; Soest et al., 2020). Using guidance from these studies as well as Wysocki et al. (2022), the current study does not distinguish between predictors and covariates and treats all factors as potential moderators of loneliness trajectories. This deviates from the preregistration and is disclosed for transparency in the deviations table (see Table S1 in the Supplemental Material available with the online version of the article; Willroth & Atherton, 2024). Thus, we present fully adjusted models here but also provide unadjusted results and exploratory analyses with covariate-by-slope interactions (see online supplementary materials at https://emoriebeck.shinyapps.io/loneliness-trajectories/).

Additionally, the current set of potential moderators is modeled strictly at baseline. We acknowledge that most of these predictors are not static but, rather, dynamic over the life span. As such, we caution against overinterpreting these models.

Social-isolation measurement differed across studies but involved selecting and harmonizing baseline items reflecting respondents' frequency of social contact. HRS participants were asked whether they had weekly social contact with parents or children (individual items), whether they engaged in social activities, and whether they lived alone. ELSA participants were asked whether they had weekly contact (in person, by phone, or via email) with their children or parents (individual items), whether they participated in weekly social activities, and the number of people living in their household (dichotomized into living alone or not). SHARE participants were asked the same items as ELSA participants, except rather than asking about weekly social activities, they were asked about yearly social activities. GSOEP participants were asked how frequently they attended social gatherings, had contact with friends abroad, visited family members, and the number of people living in their household (dichotomized into living alone or not). HILDA participants were asked how frequently they visited family members, friends, or neighbors not living with them, contacted their children (in person or by letters, email, or phone), contacted their parents (in person or by letters, email, or phone), and the number of people living in their household (dichotomized into living alone or not). SATSA participants were asked how frequently they contacted their twin (in person or via phone or letters), met or spoke on the phone with friends, and the number of people living in their household (dichotomized into living alone or not). Octo-Twin participants were asked how frequently they saw other people, phoned or saw their children or grandchildren, phoned or saw their twin, and whether they lived alone or not. LISS participants were asked how frequently they contacted their mother or father (via phone or email or in person), spent time with family members not in their household, spent time with friends or neighbors, and the number of people living in their household (dichotomized into living alone or not). SHP participants were asked how frequently they had contact with close friends, were invited out by friends, had contact with their children, participated in religious services, had contact with their neighbors, and the number of people living in their household (dichotomized into living alone or not). Across studies, individual items were binary coded (1 = higher isolation). Scores were summed (range 0–4), then $z$-transformed for cross-study comparison (see the supplemental material for a detailed table of all social isolation items across studies).

Sex was coded as 1 = female and 0 = male.

Marital status at baseline for each study was recoded such that 1 = partnered or married, 2 = divorced or separated, 3 = widowed, and 4 = never married. Married was used as the referent group in analyses.

Education was assessed by asking participants to report the total number of years of education they had received. In LISS, HILDA, SATSA, and SHP, education was coded as school levels or degrees, which were converted into years of education using metrics for each country. To optimize the comparability of this variable, education level was $z$-scored for analysis.

Functional limitations were assessed at baseline using items that captured participants' activities of daily living and instrumental activities of daily living. We identified items that were common across studies to create a single indicator of functional limitations within each study. If not already assessed as whether (1 = yes, 0 = no) the respondent had difficulty completing each task, the items were transformed to binary indicators. The following tasks were used: getting dressed, bathing/showering, eating, getting in/out of bed, managing money, taking medication, shopping for groceries, and preparing a hot meal. For each study, we summed all items together into a single indicator (where higher scores indicated more functional limitations) and $z$-transformed it for cross-study comparability.

Age was modeled in three ways to capture the three nested levels (observation, person, study). First, within-person age was centered at 60 years and included as the temporal metric in longitudinal models to evaluate whether individuals' loneliness scores change as a function of their increasing age over time. Second, between-person age was operationalized as participant age at the first loneliness assessment per study, included as a predictor allowing tests of whether baseline age impacts mean loneliness levels and/or rates of change over time. Finally, average baseline sample age per study was utilized in meta-regression models to determine if cross-study variation in loneliness trajectories relates to average study-level age. This three-pronged age specification enables distinguishing longitudinal versus cross-sectional age differences in loneliness as well as comparing current findings with prior cross-sectional work on age and loneliness.

Income was assessed at baseline within each study as yearly earnings and was $z$-transformed for analysis.

Smoking status was assessed at baseline within each study and coded as 1 = current smoker and 0 = nonsmoker.

Drinking status was assessed at baseline within each study and coded as 1 = drinks alcohol and 0 = does not.

Body mass index (BMI) was assessed via self-report in each study at baseline, expressed as kg/m$^2$.

Chronic conditions were assessed via self-report, with respondents indicating whether (1 = yes, 0 = no) they had ever been diagnosed with specific conditions. We selected three conditions—hypertension, diabetes, and heart condition—because they were assessed across all studies.

Depression was measured using one item capturing whether participants felt depressed. Some studies (e.g., HILDA) used binary (0 = no, 1 = yes) response options, and others (e.g., HRS, ELSA, SHARE, GSOEP, LISS, SATSA, Octo-Twin, and SHP) used longer, Likert-like response options (e.g., ranging from 0 = *rarely* to 3 = *most or all of the time*). All were recoded as binary variables such that 0 = no depression and 1 = some or many depressive symptoms.

Mental orientation was collected at baseline for each study and was a summary score of whether the respondent was able to correctly identify the current day, month, year, and day of the week. Some studies did not have mental orientation measures. For these studies, we included a self-rated intelligence item (*z*-scored; HILDA, GSOEP, LISS) or omitted the covariate (SHP).

Episodic memory was assessed at baseline for each study in which it was available (HRS, SHARE, ELSA, SATSA, Octo-Twin) and was a standardized average of immediate and delayed word recall tasks.

## Individual study analysis

A series of multilevel growth models were used to evaluate loneliness patterns and baseline predictor associations within each study. The models were built from the least to the most complex, starting with the unconditional random-intercept model, expressed as $Y_{ti} = \pi_{0i} + \varepsilon_{ti}$, where $Y$ is the loneliness score at a given measurement occasion $t$ for person $i$. This model provided an estimate of the intraclass correlation (ICC), which is the proportion of the variation in loneliness scores due to within- versus between-person differences. Next, we modeled change in loneliness, using age as the time metric, centered at 60 across studies to facilitate between-study comparisons and more easily allow us to compare older and middle adults. We added the fixed and random effects of age in a stepwise fashion to estimate loneliness change over time and to account for individual differences in change over time, respectively.

We subsequently added baseline predictors (i.e., social isolation, gender, baseline age, marital status, functional limitations, depression, smoking, drinking, income, chronic conditions, BMI, episodic memory, and mental status) to test whether these factors are associated with overall levels of loneliness. We used imputation to deal with missing data for predictors. In order to evaluate the possibility of nonlinear trajectories, we included a set of models with the quadratic time effect ($age^2$). Last, we included interactions between our baseline predictors and age/$age^2$, to assess whether these predictors are associated with change in loneliness over time. For all models including the quadratic term, we also included the lower-order interaction. The likelihood ratio test comparing the model fits for the linear versus the quadratic models suggests that the quadratic models were a better fit to the data across all datasets. Later, we report the overall trajectories for both the linear and quadratic models but report only the predictors of quadratic change given that the quadratic trajectory was the best-fitting model. Other results are available in the online materials and web app (https://emoriebeck.shinyapps.io/loneliness-trajectories/).

## Meta-analysis

Results from the individual study analyses were exported for use in the meta-analysis and summarized. We used random-effects meta-analysis (RMA) to calculate the overall weighted mean effect sizes, standard errors, and 95% confidence intervals across studies for loneliness levels and changes. To examine between-study heterogeneity of effects, we report estimates of Cochran's $Q$ and $I^2$ that were calculated as part of the RMA. Study-level moderators were not formally included in the meta-analysis because of low study-level power.

## Transparency and openness

Raw data for the current analyses can be requested through the individual study sites. We report all measured variables assessed across studies that are relevant to the current research, describe how the sample size was determined, and outline exclusions of variables in our statistical models. We follow Journal Article Reporting Standards (Appelbaum et al., 2018). Data analyses were completed in R (R Core Team, 2020) with the following packages: tidyverse (Wickham, 2019), psych (Revelle, 2021), kableExtra (Zhu, 2021), readxl (Wickham & Bryan, 2019), haven (Wickham & Miller, 2020), lme4 (Bates et al., 2015), broom.mixed (Bolker & Robinson, 2020), metafor (Viechtbauer, 2010), mice (van Buuren & Groothuis-Oudshoorn, 2021), plyr (Wickham, 2020), and furrr (Vaughan & Dancho, 2021). Primary hypotheses, the full preregistered analytic plan, participant eligibility criteria, criteria for inferential statistics, and analytic scripts in R can be found on the Open Science Framework at https://osf.io/67tfa/?view_only=9c3bc61fdf864c67ab30fcdf160c6280. Rendered results are available as part of an R Shiny web app at https://emoriebeck.shinyapps.io/loneliness-trajectories/.

There are a few deviations from the preregistration worth noting. First, the preregistration states that the loneliness outcome would be binary and that the model estimates would be converted to odds ratios. This was written in error, as the UCLA Loneliness Scale is not binary, and consequently, the model estimates were also not converted to odds ratios. Second, our stated prediction that loneliness would follow an inverted-*U*-shaped trajectory was made in error, as we intended to specify a *U*-shaped prediction. As such, in our results, we focus on the overall pattern of the trajectory and less so on a confirmatory statistical test. Last, we conducted a preliminary round of preregistered analyses (https://osf.io/67tfa/?view_only=9c3bc61fdf864c67ab30fcdf160c6280) using three longitudinal samples: ELSA, HRS, and SHARE. Each of these studies is part of the HRS international family of studies, and datasets were identified via the Gateway to Global Aging Network. In this initial round of analyses, our minimum inclusion requirement for eligibility was at least three measurement occasions of loneliness assessed using the UCLA Loneliness Scale (Hughes et al., 2004). We later expanded our inclusion criteria to include studies measuring loneliness using the CES-D loneliness item (Brantley et al., 2000). Five additional datasets met the new inclusion criteria: GSOEP, HILDA, Octo-Twin, SATSA, and SHP. We also identified one study, LISS, that used a Rasch-type scale of loneliness that we opted to include because of its similarity to the UCLA scale. The analyses reported later are identical to those proposed in the original preregistration.

The datasets included in this CDA have published works on loneliness (see individual study websites for comprehensive lists of published research associated with each dataset). Using the ELSA data, inflammation was related to the onset of loneliness (Vingeliene et al., 2019), and also loneliness was associated with memory function (Yin et al., 2019). This paper also found that ELSA participants reported a linear increase in loneliness and a small inverted-*U*-shaped curve in loneliness. The current study uses additional waves of ELSA data to replicate these findings. In GSOEP, using two waves of the UCLA Loneliness Scale, it was found that older adults experienced higher loneliness (Schübbe et al., 2022). The current study uses additional waves to model change in loneliness. Two studies using HILDA found associations among age, health, loneliness, and well-being (Tani et al., 2020) and identified that an increasing number of people are experiencing high loneliness (Baker, 2012), but neither explicitly modeled trajectories of loneliness over time. In HRS, growth-mixture models were used to identify clusters of individuals experiencing different loneliness trajectories in older married couples (Ermer et al., 2020). Another more recent article examined associations among trajectories of loneliness and cognitive impairment using three waves of loneliness data, finding a linear increase (Lee et al., 2022). We replicate and extend this work by using the fourth measurement occasion of loneliness to model the nonlinear pattern in addition to the linear. In LISS, a propensity-score-matched study of loneliness change found that loneliness did not change in this particular sample (Buecker et al., 2021). In Octo-Twin and SATSA, it was found that loneliness follows a *U*-shaped curve, swinging up after age 60 (Kim et al., 2021; Phillips et al., 2022). In SHARE, late-life loneliness was related to educational and family factors, but loneliness trajectories were not formally tested (Fernández-Carro & Gumà Lao, 2022). Last, to our knowledge, SHP has not used its longitudinal loneliness data in any formal published analysis (https://forscenter.ch/projects/swiss-household-panel/). In summary, although several datasets here have modeled loneliness change, the current study extends prior work by reproducing, replicating with additional waves and samples, and harmonizing analytic models to provide a cohesive picture of loneliness change. This can elucidate potential mechanisms and intervention targets.

## Results

Before testing our primary research questions, we first examined the unconditional, intercept-only models. The ICCs from the intercept-only loneliness models ranged from .29 to .61 across samples, indicating moderate to substantial within-person variability over time.

### *How does loneliness change with age?*

To test whether loneliness changes across the life span, we ran a series of multilevel linear growth models. We scaled the growth models according to centered age in years (transformed into decades to assist with model convergence), which yielded linear estimates of loneliness change over time. Results suggest that individuals report becoming more lonely with age, and this effect is consistent in both direction and magnitude across studies with a few exceptions. The meta-analytic summary indicates a positive effect of age, suggesting that loneliness increases over time. For the studies using a single-item measure of loneliness, we opted to examine test–retest correlations as an indicator of longitudinal consistency. For shorter time intervals (1–3 years), test–retest consistency was above 0.4. Even for longer time intervals (> 5 years and often > 10 years), test–retest consistency remained above 0.2. Heat maps of test–retest consistency for each of these studies are available in the online materials and R Shiny web app (https://emoriebeck.shinyapps.io/loneliness-trajectories/). As

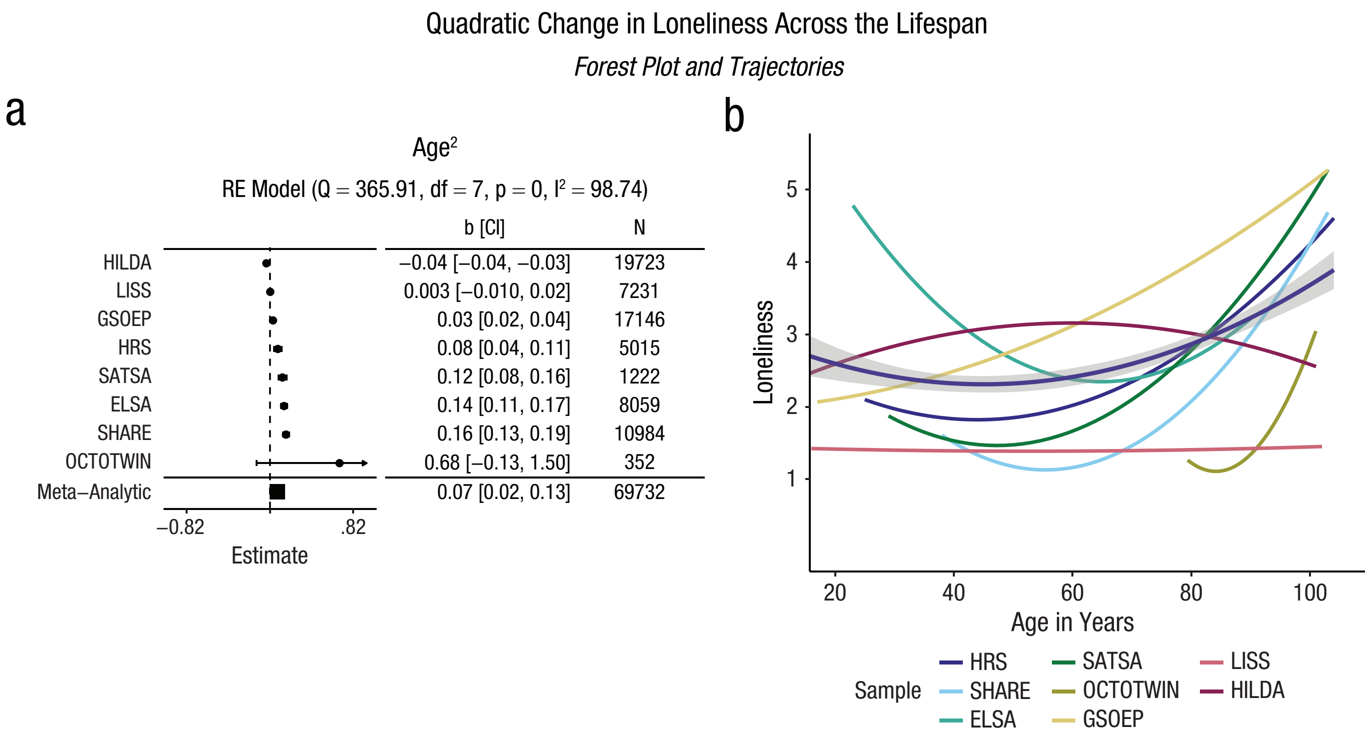


**Fig. 1.** Quadratic trajectories of loneliness over time. Point estimates (circles) for each study represent the results from longitudinal models including only data for that study. Error bars indicate 95% confidence intervals (CI) around those effects. Meta-analytic estimates were derived from random-effects meta-analysis. In the right panel, black line displays the meta-analytic average, and colored lines display the trajectories within each study.

an additional robustness test, we conducted a series of metaregression models to examine whether sample- and study-level characteristics may explain different-shaped trajectories across samples. Specifically, we examined whether sample-level linear and quadratic slopes could be predicted from (a) continent of data collection, (b) baseline year of data collection, (c) the number of measurement occasions, (d) the interval (in years) between measurement occasions, (e) the interval between first and last assessment, and (f) the loneliness scale used. We did not find evidence of moderators of linear change for any of our key study-level factors, including continent, number of measurement occasions, or interval (time) between measurement occasions (see next paragraph for quadratic change findings). These results suggest that linear change in loneliness is relatively consistent across contexts (e.g., continents) and according to various research design characteristics (e.g., assessment type and both number and frequency of measurement occasions).

To test whether nonlinear trajectories better describe changes in loneliness across the life span, we added quadratic age to the model. The meta-analytic summary indicated a nonlinear pattern of loneliness ($B$ = 0.07, $SE$ = 0.03, $p$ = .01). See Figure 1a for the individual study estimates and meta-analytic summary. Results generally indicated a positive effect, revealing a *U*-shaped curve, in which individuals tended to decrease in loneliness until approximately age 50 and then increased thereafter (see Fig. 1b). Although the effects varied at the individual study level, most showed a consistent and statistically significant partial *U*-shaped pattern, with three exceptions. The quadratic age effects were nonsignificant for LISS and Octo-Twin, whereas HILDA showed an inverted-*U* shape. We found evidence for study-level moderation in the meta-analyses for the quadratic models. According to the metaregression analyses, we found evidence suggesting that wide intervals between measurement occasions was associated with more bend in the *U* curve, whereas studies with more measurement occasions had less bend. This might suggest that studies with more measurement occasions and shorter time intervals between measurements are likely better suited to modeling nonlinear effects. It is also possible that loneliness changes more over long time intervals or that the estimates are reflecting change per year. In future data collection efforts, researchers should take this into account when designing their studies. This matches what is presented in the forest plots. In summary, loneliness appears to either remain low or decrease during middle adulthood, prior to sharply increasing in older adulthood.[1]

### *Do sociodemographic and health factors predict loneliness?*

We examined whether sociodemographic and health factors predict mean loneliness levels. We acknowledge that most of these predictors are not static but in fact likely dynamic over the life span. As such, we caution against overinterpretation of these models. Results showed consistent evidence for higher loneliness among individuals reporting less social contact, identifying as female, being younger at baseline, being divorced or widowed (vs. married), and having less education, greater functional limitations, lower income, less drinking, more smoking, higher depression, higher BMI, lower memory, and more chronic conditions. Figures 2 and 3 show forest plots of study-specific and meta-analytic effects for each predictor of loneliness levels, along with additional metrics for the meta-analytic results (e.g., Cochran's *Q*). See the supplemental online material for the full model summaries. For individuals who were never married, the meta-analytic estimate indicated no effect on loneliness levels; however, several individual studies found an effect suggesting that being never married is also associated with higher loneliness. For all predictors, the evidence was consistent across studies, with most studies showing estimates in the same direction and of similar magnitude.

***Do sociodemographic and health factors predict changes in loneliness?*** To test whether baseline sociodemographic and health factors predict linear and nonlinear changes in loneliness, we added them as cross-level interactions with the age time variable (i.e., predicting the person-level slope). The interactions among all baseline predictors and quadratic age were mostly null across studies and for the meta-analytic summary, indicating that individual differences in social isolation, sex, marital status, functional limitations, education level, income, health behaviors (smoking, drinking), mental health, cognitive health, and physical health were not associated with quadratic changes in loneliness with age (see Figs. 4 and 5). There was one exception: a small effect of baseline age on quadratic change in loneliness. Individuals who were under 60 at baseline may increase in loneliness through middle adulthood and then become less lonely at old age (see Figure 6). To test the extent to which risk factors are associated with change in loneliness across age groups, we conducted a series of additional models testing interactions between baseline age and each of the risk factors. As shown in the forest plots in the online materials and R Shiny web app, none of these were significant in the core models, which suggests that the effect of these risk factors on these loneliness trajectories does not vary by age at baseline.

## Discussion

This study employed coordinated data analysis to explore longitudinal patterns and predictors of loneliness across nine independent studies from various countries. The findings revealed a partial *U*-shaped curve in loneliness, with levels declining from young adulthood to midlife and increasing in older adulthood. This pattern held across nine heterogeneous studies from multiple nations and could not be fully explained by baseline demographics or health. Additionally, being socially isolated, female, less educated, and physically limited predicted higher loneliness levels. However, few baseline factors forecasted shifts in loneliness over lengthy follow-up.

The observed trajectories align with earlier research (Lay-Yee et al., 2021; Mund, Freuding, et al., 2020; Nyqvist et al., 2016; Perlman, 1990) and theories linking developmental social role changes to life span loneliness (Akhter-Khan et al., 2023; Baltes & Carstensen, 1999; Carstensen et al., 1999). Younger adults may experience higher loneliness levels due to challenges in establishing their identity, career, and intimate relationships. By midlife, social networks and roles may be more stable and satisfying. Later-life increases could reflect lost relationships and resources.

In a recent meta-analysis, Mund, Freuding, et al. (2020) addressed similar questions as the current study and used traditional meta-analysis to draw their conclusions. They examined similar research questions but incorporated childhood and adolescence in documenting an inverted-*U*-shaped loneliness curve. Our focus on adulthood aligns with the *U*-shaped pattern evident for this period in their visualizations. This convergence using distinct synthesizing approaches highlights the value of complementary metascientific tools. While findings are often congruent, the occasions when findings are divergent can advance understanding and provide a more nuanced knowledge base. This lends credence to the idea that traditional meta-analysis and CDA are very different but complementary tools for synthesizing findings across disparate data sources. Often, we find similar results, but even when we do not, there is still knowledge to be gained.

The replicated *U* curve supports loneliness as a developmental phenomenon varying by life stage across cultural contexts. However, baseline age moderation suggests potential generational or timing effects. Younger baseline samples showed lower loneliness,

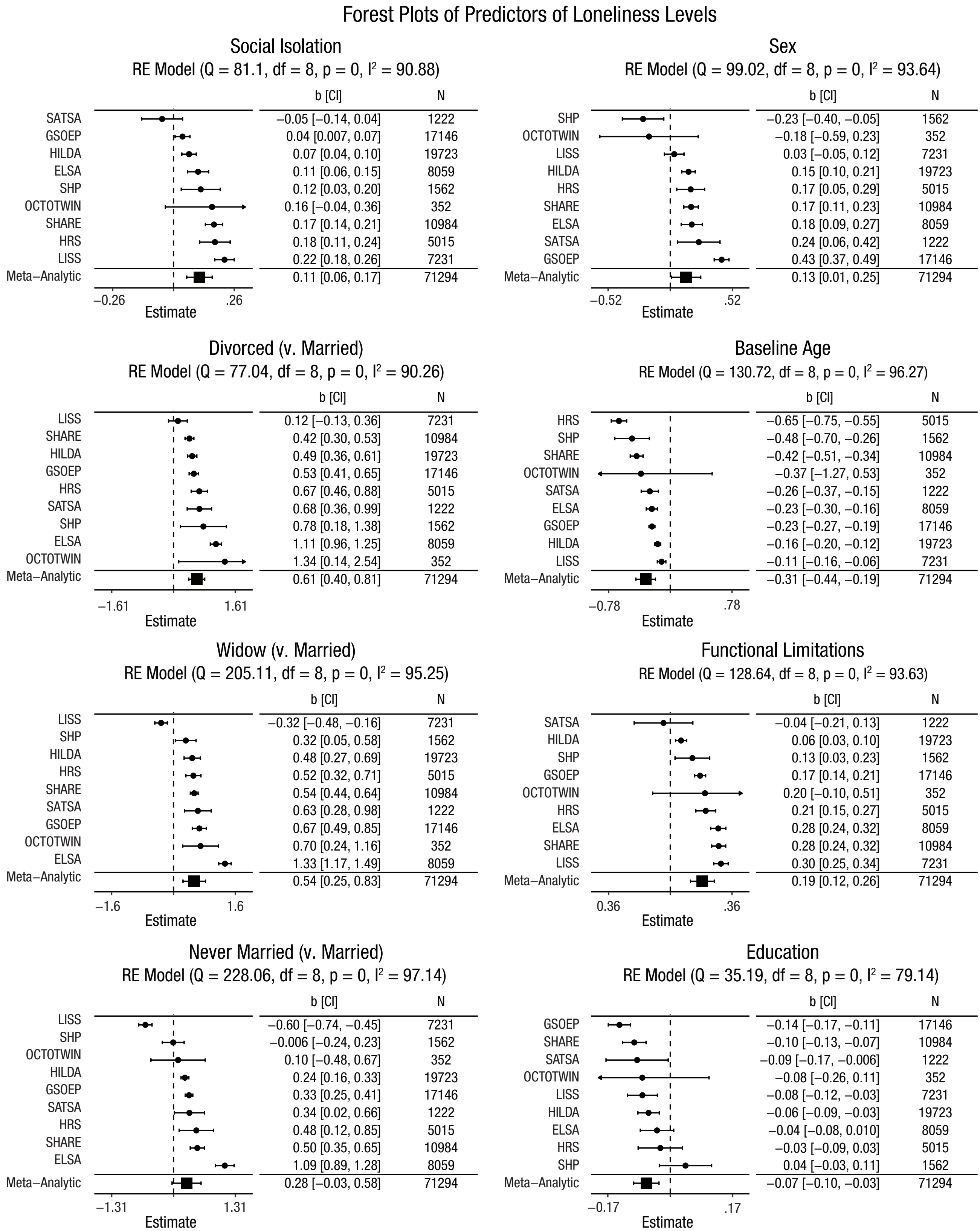


**Fig. 2.** Associations among key baseline predictors and overall levels of loneliness across studies (Part 1). Point estimates (circles) for each study represent the results from longitudinal models including only data for that study. Error bars indicate 95% confidence intervals (CI) around those effects. Meta-analytic estimates were derived from random-effects meta-analysis.

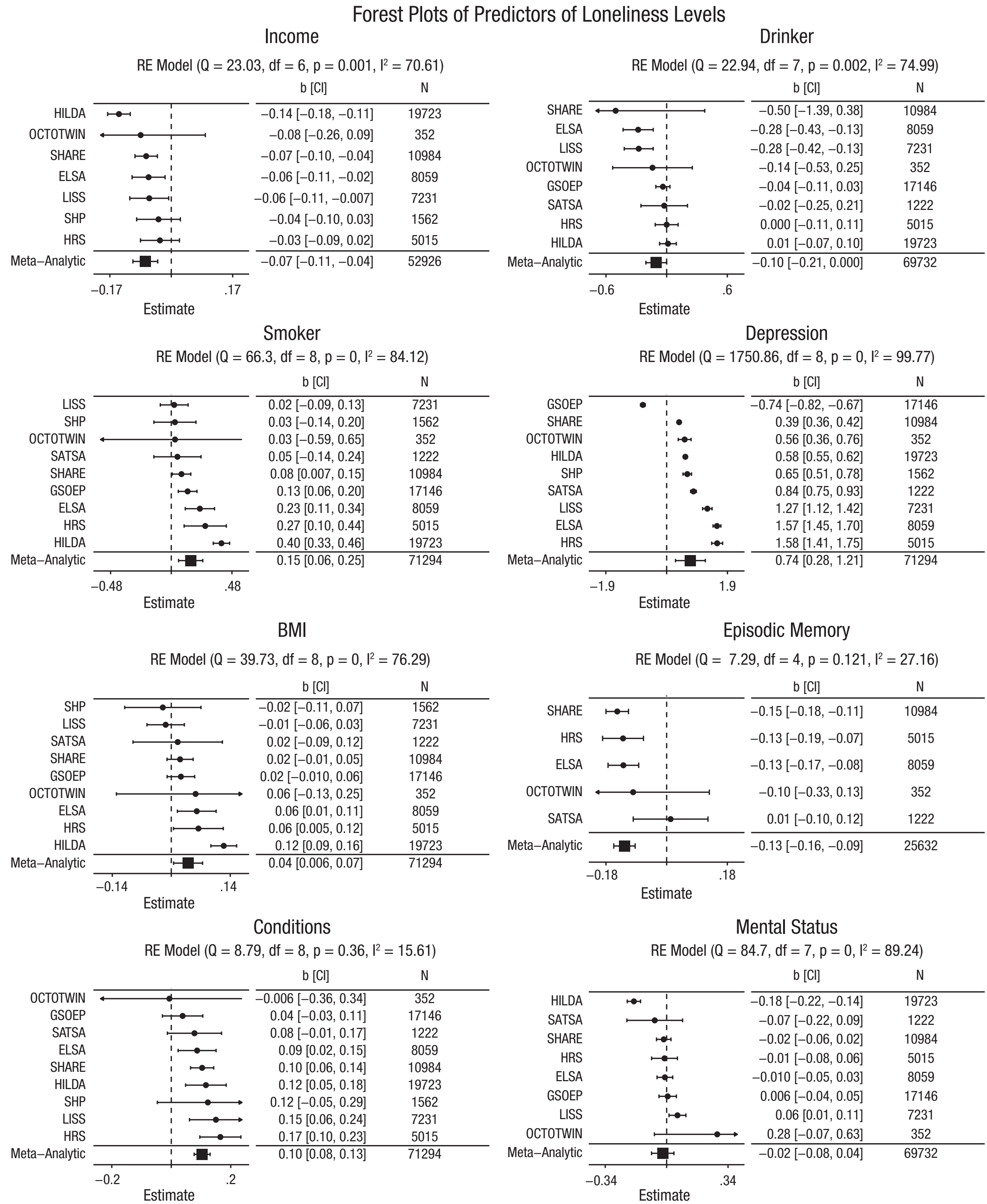


**Fig. 3.** Associations among key baseline predictors and overall levels of loneliness across studies (Part 2). Point estimates (circles) for each study represent the results from longitudinal models including only data for that study. Error bars indicate 95% confidence intervals (CI) around those effects. Meta-analytic estimates were derived from random-effects meta-analysis.

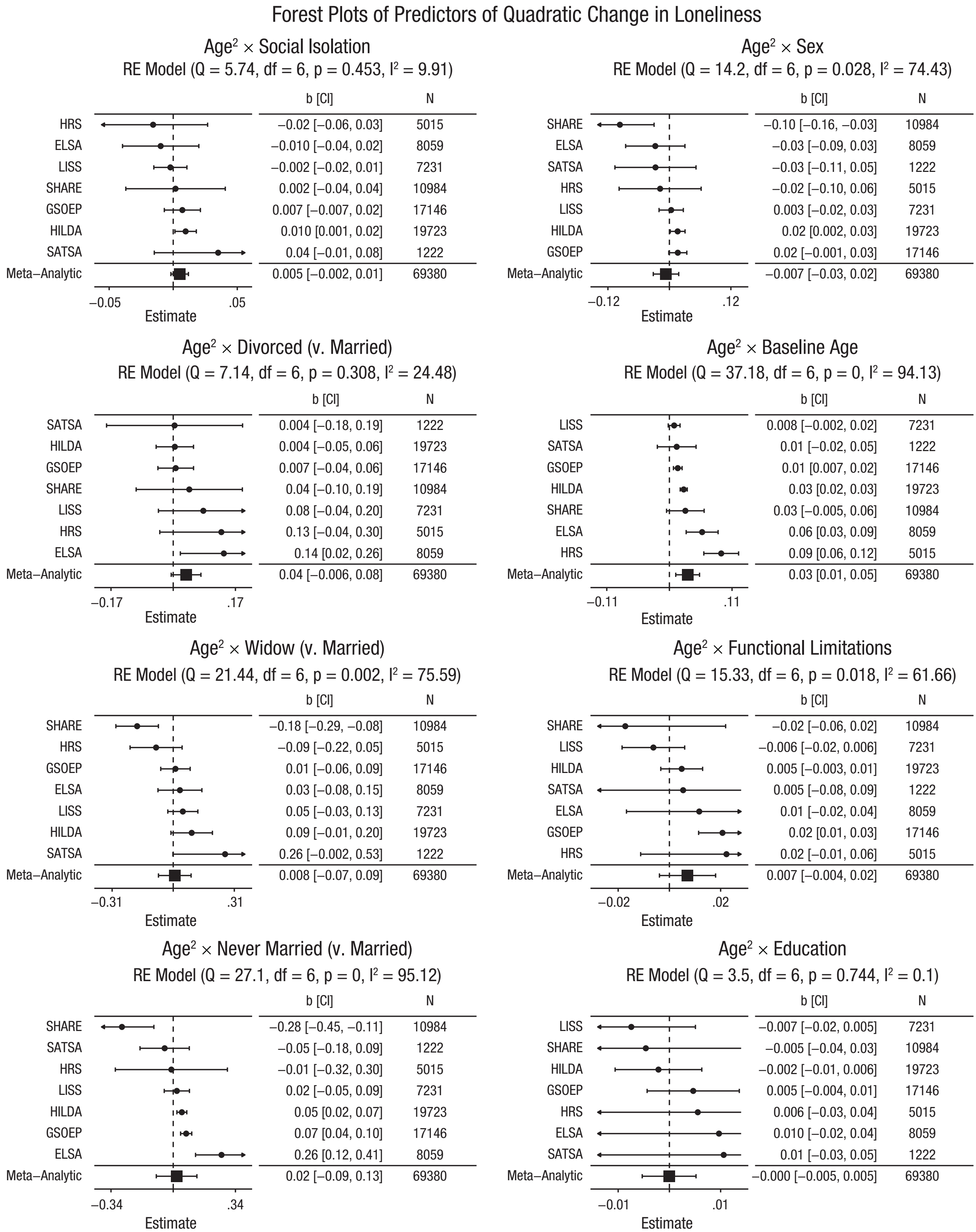


**Fig. 4.** Associations among key baseline predictors and nonlinear change in loneliness (Part 1).

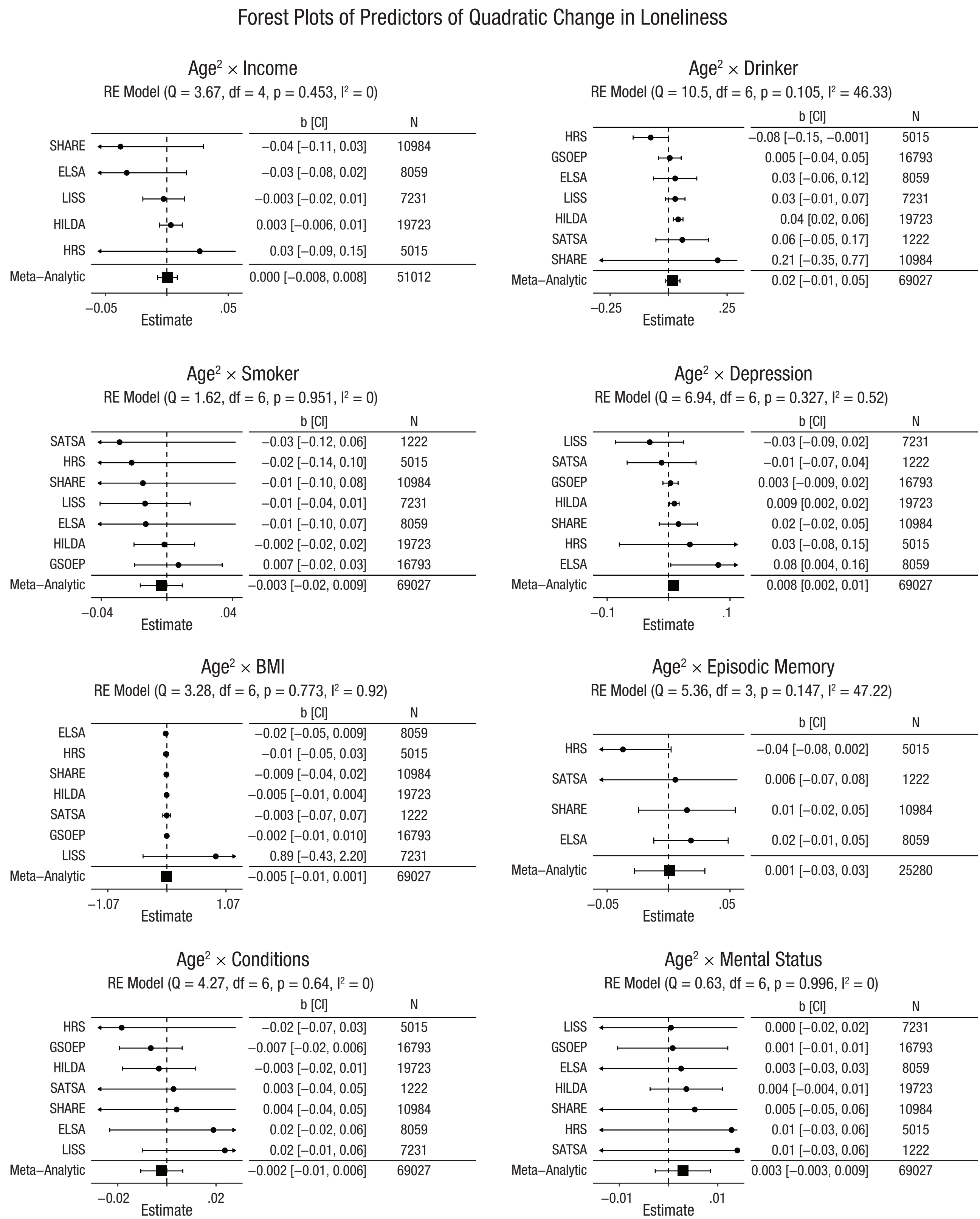


**Fig. 5.** Associations among key baseline predictors and nonlinear change in loneliness (Part 2).

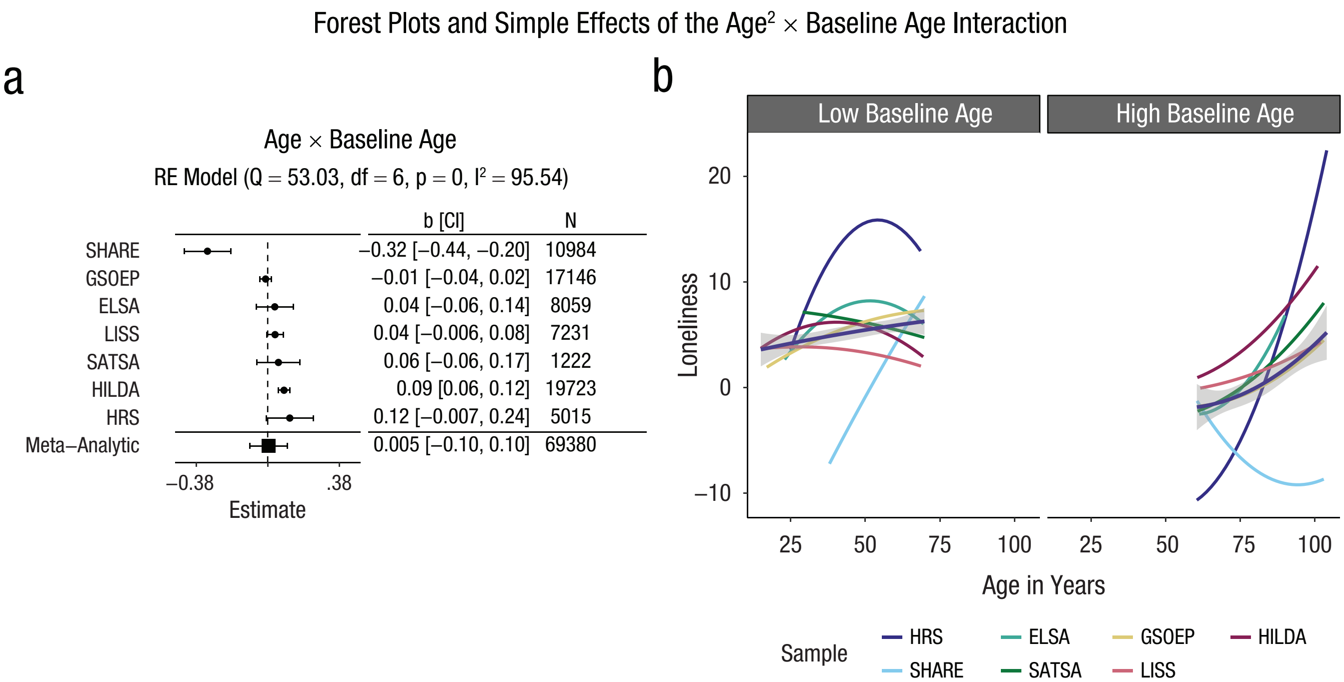


**Fig. 6.** Quadratic trajectories of loneliness over time, moderated by baseline age. Black line displays the meta-analytic average.

perhaps reflecting cohort differences in experiences or expressions (Hülür et al., 2016; Suanet & van Tilburg, 2019). Alternatively, nonlinear trends may depend on measurement timing or duration. Additional long-term multiwave studies can further disentangle these complex dynamics.

## *Predictors of loneliness levels and changes*

The results showed that individuals who were more socially isolated, female, younger, and less educated and had more functional limitations, lower income, less drinking, more smoking, higher depression, higher BMI, lower memory, and more chronic conditions at baseline reported persistently high loneliness levels on average. These effects were also consistent in magnitude and direction across studies, providing robust evidence about who is at higher risk of experiencing loneliness.

The results align with existing literature identifying social isolation and several sociodemographic factors as risk factors for loneliness in older adults (Dahlberg et al., 2022). Lower education and poor functional status have been linked to higher loneliness (Cohen-Mansfield et al., 2016), reflecting lower socioeconomic resources and opportunities for social participation and support, which may contribute to social isolation and perceived loneliness. Moreover, bidirectional or cyclical relationships between functional disability, limited socioeconomic resources, and loneliness could exacerbate social isolation, resulting in further perceptions of loneliness (Ong et al., 2016). Women may experience more loneliness than men because of their greater tendency to internalize negative emotions and their increased sensitivity to changes in social relationships (Maes et al., 2019). Additionally, younger adults may experience more loneliness than older adults because of challenges in transitioning into adulthood and establishing social identities (Luhmann & Hawkley, 2016).

Contrary to hypotheses, predictors minimally forecasted loneliness changes over time. The dynamic nature of these factors and their context-dependent effects may contribute. Most critically, idiosyncratic differences likely render between-person approaches limited for capturing intricacies and fluidity in subjective loneliness experiences (Beck & Jackson, 2020, 2022).

## *Limitations and future directions*

Several limitations of the present study warrant mention. First, we focused solely on baseline predictors; however, most factors likely fluctuate over time and interact in complex ways to shape dynamic loneliness. Future work should explore how changes across aging in social ties, marital status, disabilities, depression, and other variables interrelate with loneliness trajectories. Analyses also did not account for relationship quality, which could critically impact social support availability and loneliness perceptions (Shiovitz-Ezra & Leitsch, 2010). Research shows older adults prioritize emotionally meaningful bonds (Carstensen et al., 1999), so accounting for this qualitative shift may reveal developmental nuances.

Although we examined baseline age variations, outstanding questions remain around disentangling complex period and cohort dynamics (Bell, 2014; Luhmann et al., 2023). Though modeling baseline age variations provided initial insight, fully disentangling cohort effects necessitates complex age-period-cohort analysis. Clarifying effects from life course fluctuations in these changeable predictors also requires a widened methodological scope.

Given the possibility that our selected predictors may show fluctuation over time, additional work is needed to relate this change to loneliness patterns. The current study has provided basic information on whether a person's incidental status at baseline on a given predictor is associated with their loneliness trajectory, and we are limited in our ability to interpret this longitudinally (e.g., how stable these predictors are over time). As such, we caution against overinterpreting these preliminary findings and urge exploration of the complex, reciprocal interplay among factors driving changes in perceived isolation. Such multifaceted modeling extends beyond the current scope but remains crucial for elucidating the full intricacies of situational and individual drivers underlying loneliness.

Furthermore, considerable variability emerged across studies, likely reflecting heterogeneous designs, samples, measures, and cultural contexts. Thus, observed effects could stem from unmeasured confounds or moderators. Future work should examine how study-level characteristics influence loneliness associations. Finally, we employed a meta-analytic approach for synthesizing coordinated findings, which offers several advantages, including harmonizing variables and models, enhancing replication and generalization, and reducing publication bias (Graham et al., 2022; Hofer & Piccinin, 2009). However, this approach also has limitations, such as relying on existing data sources that may not have optimal measures or designs for answering research questions and requiring a high level of coordination and collaboration among researchers from different studies.

### *Constraints on generality*

The studies used in the current coordinated data analysis were not necessarily comprehensive, and the studies included tended to be from Westernized, educated, industrialized, rich, and democratic countries. Our results may not generalize to non-Western or developing countries. Because there was little evidence that the loneliness scales used in the present study varied systematically, we believe these results would generalize to other measures of loneliness that were not used in the present study. These results may not generalize across birth cohorts or different historical periods that similar data may be or have been collected. Because attrition causes biases in results, the current findings may not generalize to individuals who dropped out of the study.

## Conclusion

This study provides a comprehensive and coordinated analysis of loneliness trajectories and predictors across nine longitudinal studies from various countries. The findings demonstrate a partial *U*-shaped pattern of loneliness across adulthood, with higher levels in young and older adults than in midlife adults. This pattern replicated across studies and cannot be explained by baseline demographics or health. Results further identified several risk factors for heightened loneliness, including social isolation, sex, education, and physical impairment. However, few predictors of changes in loneliness over time were found, suggesting that loneliness is a complex and dynamic phenomenon that requires more nuanced and individualized approaches to understand and intervene. Future research should address the limitations of this study by incorporating more dynamic and contextual measures of loneliness and its predictors.

**Transparency**

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*Declaration of Conflicting Interests*

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

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*Open Practices*

The hypotheses and methods were preregistered (https://osf.io/67tfa/?view_only=9c3bc61fdf864c67ab30fcdf160c6280) prior to data analysis. There were deviations from the preregistration (for details, see Table S1 in the Supplemental Material available online). Data are available for download on the individual study websites. All analysis scripts are publicly available (https://osf.io/67tfa/?view_only=9c3bc61fdf864c67ab30fcdf160c6280). No artificial intelligence–assisted technologies were used in this research or the creation of this article. This research used fully deidentified existing data and as such was not considered human subjects research. This article has received the badges for Open Materials and Preregistration. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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## Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976241242037

## Note

1. For additional descriptive robustness tests of shape of the trajectories, we conducted two additional tests: cross-sectional age differences and generalized additive models (GAMs). First, we examined cross-sectional age differences of loneliness across the life span in each sample. Second, we used GAMs to estimate a nonlinear pattern across the life span in each study. Overall, both methods supported quadratic models as the best-fitting models across samples. The figures can be seen in the online materials and web app: https://emoriebeck.shinyapps.io/loneliness-trajectories/.

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