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Personality and Mortality Risk: A Systematic Review and Meta-Analysis of Longitudinal Data

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Personality traits have long been deemed to be an important driver of longevity; however, a large volume of evidence remains divergent across traits, populations, and contexts. This preregistered systematic review and meta-analysis brings together longitudinal data (158 effect sizes) exploring five personality trait associations with mortality risk from 569,859 people, representing 5,997,667 person-years, 43,851 deaths, and four continents. Univariate and multivariate meta-analyses were conducted. Neuroticism predicted an increased risk of premature death, while extraversion and conscientiousness predicted reduced mortality risk. For neuroticism, age was a significant moderator, such that the effects were stronger for younger populations. Adjustment for health-related factors reduced the effects of neuroticism and conscientiousness on mortality risk. Extraversion had a significant protective effect only in pooled samples from North America and Australia. Significant effects for openness did not withstand small-study bias adjustment. No association was found for agreeableness. Multivariate analyses revealed that each of the significant effects for neuroticism, extraversion, and conscientiousness persisted when adjusting for all traits. Several trait groupings were tested to compare how well they predicted mortality risk. The Five-Factor Model demonstrated the most parsimonious explanation. This review amalgamates extensive longitudinal work and highlights the critical role that personality plays in longevity.

Keywords: personality, mortality, neuroticism, conscientiousness, extraversion

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A link to preregistration, all meta-analytic data, analysis code, and research materials is available on the Open Science Framework (https://osf.io/f2knr/; McGeehan et al., 2025). Preliminary findings were presented at the American Psychosomatic Society Annual Meeting, March 21, 2024, in Brighton, United Kingdom, and at the European Association of Personality Psychology conference, August 9, 2024, in Berlin, Germany.

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continued

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Human curiosity about how individuals are different from one another has long been a topic of considerable interest, particularly in terms of how long we live. The notion that our personality can predict how long we live persists from the early philosophy of ancient Greece to modern psychology (Irwin, 1947). Since we could not evolve a trait that is adaptive in all contexts across evolutionary time, the myriad of ways that our personality permeates our thoughts, feelings, and behavior may be a critical factor in determining our longevity. The most recognized and widely accepted conceptual framework suggests that personality traits are a core aspect of a wider personality system and can be inferred from observation of relatively stable patterns of thought, feeling, and behavior (Costa et al., 2019; Costa & McCrae, 1992a; John et al., 2008; McAdams & Olson, 2010; McCrae & Costa, 2008). Personality traits are most commonly represented as five factors that can be characterized using the following broad definitions: neuroticism, reflecting emotional stability and impulsivity; extraversion, reflecting activity and sociability; openness, reflecting willingness to experience new things; agreeableness, reflecting willingness to cooperate with others; and conscientiousness, reflecting order and self-discipline (Costa & McCrae, 1992b; H. J. Eysenck, 1958; Goldberg, 1990).

It is likely that personality is related to mortality risk via a vast array of mechanisms, including a broad spectrum of biobehavioral health processes related to a broad range of health behaviors, coping processes, stress responsivity, and biological processes (Grogan et al., 2024). Personality traits may influence engagement in behaviors that have health consequences across extended periods, ultimately influencing longevity (Turiano et al., 2021). The health behavior model describes how personality traits may influence engagement in health risks (e.g., smoking) or health-protective behaviors (e.g., physical activity; Graham et al., 2017, 2020; Hampson & Friedman, 2008; Rizzuto et al., 2017; Sutin et al., 2016; Turiano et al., 2015; Turiano, Hill, et al., 2012). Several traits have been associated with physical activity, which has been associated with disease burden and mortality risk (Allen et al., 2017; Lee et al., 2012; Sutin et al., 2016). High levels of neuroticism, characterized by tendencies toward worry, anxiety, and emotional instability, may lead to maladaptive coping behaviors such as smoking (Goodwin & Bono, 2014; Graham et al., 2017; Mroczek et al., 2009). In contrast, higher conscientiousness, associated with organization and goal-directed behavior, may support more health-promoting behaviors and a willingness to engage with healthy lifestyle choices (Gartland et al., 2021), such as medication adherence (Molloy et al., 2014), health care utilization (Atherton et al., 2024), and use of preventative cancer screenings (Aschwanden et al., 2019), critical components of a future health trajectory. Conscientiousness is also inversely related to several unhealthy behaviors: tobacco use, poor dietary habits, inactivity patterns, alcohol use, suicide, and drug use (Bogg & Roberts, 2004).

Biological processes have been suggested as one potential cluster of mechanisms underpinning the personality–mortality risk relation (e.g., Grogan et al., 2024; O'Súilleabháin et al., 2021). Cumulative physiological arousal due to stress can adversely affect health and aging processes (McEwen & Stellar, 1993). There is a considerable body of observational and experimental research to suggest that personality traits are associated with biological and clinical markers, for example, C-reactive protein and interleukin-6 (Gallagher et al., 2021; Luchetti et al., 2014; O'Súilleabháin et al., 2021; Sutin et al., 2010; Yoneda, Lozinski, et al., 2023). These associations have been reported even at the molecular level, with personality traits associated with a measure of mitochondrial health, which in turn mediated the association between personality and mortality (Oppong et al., 2022). As such, given that these biological processes are related to physiological dysregulation that includes, for example, inflammation, hormonal balance, and cardiovascular health, which are critical to longevity, it is highly likely that personality traits are predictive of future mortality risk.

Neuroticism is considered of public health significance (Beck & Jackson, 2022; Cuijpers et al., 2010; Malouff et al., 2005; Spijker et al., 2007) and has been associated with a wide range of mental and physical disorders (Goodwin & Friedman, 2006), biological aging processes (van Ockenburg et al., 2014; Wright et al., 2022), Alzheimer's disease and dementia (Aschwanden et al., 2021, 2022; Beck et al., 2024; Terracciano et al., 2021), stress reactivity (Bibbey et al., 2013; Coyle et al., 2020; Phillips, 2011), and health behaviors (e.g., Mroczek et al., 2009). Extraversion has also been associated with cognitive health (Stephan et al., 2024; Yoneda, Graham, et al., 2023), respiratory disease (Shipley et al., 2007), health behavior (Otonari et al., 2012), stress reactivity (Lü & Wang, 2017; O'Riordan et al., 2023), and social support processes (Swickert et al., 2002). Openness has been associated with coronary heart disease (Lee et al., 2014; Weston et al., 2015), stress reactivity (Lü et al., 2016; O'Súilleabháin et al., 2018), cognitive health (Graham, James, Jackson, Willroth, Luo, et al., 2021), and biological processes (Stephan et al., 2024). Conscientiousness is the most frequently reported personality trait to be associated with a wide array of health processes and outcomes, such as health-related behaviors (Bogg & Roberts, 2004; Goodwin & Friedman, 2006; O'Connor et al., 2009; Roberts et al., 2005; Turiano et al., 2015), biological markers of health (Luchetti et al., 2014; O'Súilleabháin et al., 2021; Sutin et al., 2018; Terracciano et al., 2014), cognitive health (Graham, James, Jackson, Willroth, Boyle, et al., 2021; Graham, James, Jackson, Willroth, Luo, et al., 2021; Jackson et al., 2015; Sutin, Aschwanden, et al., 2022; Sutin, Brown, et al., 2022; Sutin, Stephan, et al., 2022; R. S. Wilson et al., 2007), stress (Gartland et al., 2012, 2014), and so on. Most studies found weak or no association between agreeableness and health outcomes.

Critical period models of personality suggest that individual differences in personality traits play a role during important moments of transition, for example, adolescence, in shaping developmental and health outcomes (Friedman et al., 2014; Hampson & Friedman, 2008).

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In addition, the cumulative impact of experiences, resources, and skills collectively shapes development and outcomes across the lifespan (Hampson & Friedman, 2008). Lifespan developmental approaches propose that how individuals adapt to age-related challenges determines where they prioritize and focus their resources (Baltes, 1997). These approaches emphasize the interactions between biological, psychological, and social factors in shaping individuals' developmental trajectories and understanding how early developmental factors may interact with personality traits (Baltes et al., 1980). The personality–mortality risk relation can therefore be understood through the impact at both critical points and cumulatively across the lifespan.

Past reviews have identified significant associations between personality factors and mortality risk. Roberts et al. (2007) combined data from four studies on conscientiousness, 12 on neuroticism, six on extraversion, and 19 on hostility/disagreeableness (low agreeableness). That review included several conceptualizations of personality; for example, items for neuroticism included mental instability, pessimism, and sense of coherence. They reported a protective association for conscientiousness and extraversion/positive emotionality/optimism. Neuroticism/negative emotionality and hostility/disagreeableness were associated with a diminished lifespan. Kern and Friedman (2008) conducted a meta-analysis of 19 studies exploring conscientiousness and mortality risk. They reported a positive association between higher conscientiousness and longevity. A review and meta-analysis of 11 studies by Ferguson and Bibby (2012) reported a significant protective effect for openness on mortality risk. While these reviews and numerous other pieces of research since have provided an invaluable contribution to this area and are the foundation we are building upon, there are significant limitations that need to be overcome (e.g., broad conceptualizations of the traits).

Personality research has developed from correlational research designs, particularly with longevity outcomes, toward integrating longitudinal data and research designs that use survival analysis (Friedman et al., 1993; Graham et al., 2017; Jokela et al., 2013). This is important as conducting follow-up research on mortality risk is very demanding and time-consuming. Advances in statistical methods have allowed research to incorporate time-to-event data that retain total samples, including deceased and alive participants, and provide more predictive accuracy and can lead to better understanding and interpretation of the data (Clark et al., 2003; Costa et al., 2019). In addition, systematic review methodology is important to assess a literature base as it uses predefined protocols and search criteria for all included studies that reduce the risk of bias in the selection and analysis of studies (Higgins et al., 2024). Furthermore, the methods are clearly documented, allowing others to replicate the review and verify findings, which is critical to a transparent and rigorous science. Given the growth of studies using survival analysis, it is imperative to conduct a meta-analysis using a systematic review framework.

A systematic review and meta-analysis focusing purely on studies using longitudinal follow-up data is critical. In other words, to avoid bias, increase power substantially, provide proportionality testing, and test for temporal shifts in risk, a review of studies focused on the production of survival estimates (time-to-event) is important to provide a clear understanding of the true relationship. Capitalizing on these techniques and using data from ongoing cohort studies, some studies have taken a coordinated analysis approach to this area. For instance, a coordinated meta-analysis of 15 observational panel studies ($N = 44{,}094$) reported an overall effect for all traits except openness (Graham et al., 2017). In other coordinated analyses, only conscientiousness was reported to be associated with mortality risk in meta-analyses of seven panel studies ($N = 76{,}150$; Jokela et al., 2013) and 10 panel studies ($N = 43{,}935$; Jokela et al., 2020). Another coordinated analysis of 12 large cohort studies reported conscientiousness associated with reduced mortality risk and no consistent pattern of prediction for neuroticism (Turiano et al., 2020), with some cohorts suggesting a reduced risk of death and others demonstrating null associations. These coordinated analyses complement a large body of other existing literature.

Various other studies report differing associations. For instance, higher neuroticism was associated with increased mortality risk (Mroczek et al., 2009; O'Súilleabháin & Hughes, 2018; Shipley et al., 2007), no significant association (Almada et al., 1991; Hagger-Johnson, Roberts, et al., 2012; Iwasa et al., 2008), and protective associations (Korten et al., 1999; Ploubidis & Grundy, 2009; Weiss & Costa, 2005). For extraversion, studies reported protective associations (Rizzuto et al., 2017; Turiano et al., 2015; Yoneda, Graham, et al., 2023) and no association (Chapman & Elliot, 2019; Hagger-Johnson, Roberts, et al., 2012; Jackson et al., 2015; O'Súilleabháin & Hughes, 2018). Similarly, for openness, some studies have reported protective effects (Iwasa et al., 2008; Jonassaint et al., 2007; Taylor et al., 2009; Turiano, Spiro, & Mroczek, 2012) and no effect (Christensen et al., 2002; Weiss & Costa, 2005; R. S. Wilson et al., 2004). And, for agreeableness, some studies reported protective effects (Jackson et al., 2015; Weiss & Costa, 2005), and others reported increased mortality risk (Chapman & Elliot, 2019) and no relation (Fry & Debats, 2009; O'Súilleabháin et al., 2021). Strong evidence suggests that conscientiousness is associated with reduced mortality risk (Chapman & Elliot, 2019; Hagger-Johnson, Sabia, et al., 2012; Kern & Friedman, 2008; O'Súilleabháin et al., 2021; Terracciano et al., 2008).

Possible reasons for inconsistencies across literature may relate to many factors. For instance, it has been suggested that age may partially explain differences in effects for openness and mortality risk, with older baseline-aged participants showing a pattern of protective effects (Graham et al., 2017). Additionally, protective effects for conscientiousness may be protective for males and not for females (Taylor et al., 2009). Geographical location may also be an important factor to consider. For instance, in one coordinated analysis, differences in extraversion between U.S. and non-U.S. samples were observed, with protective effects detected for U.S. samples (Graham et al., 2017). Another study suggested that extraversion was associated with mortality risk in an Australian sample, but not in U.S. or European samples (Jokela et al., 2013). While there are many more inconsistencies in findings between geographical locations among individual studies, it is clear that it is a particularly important factor to consider. Furthermore, given that health-related behaviors and biological markers of health are more proximal determinants of mortality than personality, studies adjusting for these factors may significantly differ in their reported outcomes. This is particularly the case as many health adjustments in statistical models are likely mediators of the personality–mortality risk relation in the first instance (Grogan et al., 2024; O'Súilleabháin et al., 2018). Depression, or depressive affect, is also an important factor to consider, particularly as it pertains to findings related to neuroticism. Neuroticism appears to be particularly important

to psychopathology (American Psychiatric Association, 2022; Hakulinen et al., 2015; Kotov et al., 2010); as such, adjustment for depression may be an important driver of heterogeneity between studies. Publication year could also be related to effect sizes: Earlier studies often report larger effect sizes, while more recent studies tend to find smaller effects, a phenomenon known as the "winner's curse" (Palmer & Pe'er, 2017). Further important factors include statistical power (percentage of deceased in sample), sample size, length of follow-up, measure of personality used, and so on.

It is also important to consider that certain groupings of traits may be more influential than others as they may relate to mortality risk. Modeling traits together may provide an important insight into explanatory power in the prediction of mortality risk. For instance, despite various measurement differences, other conceptualizations of five traits as related groupings, such as α/stability (agreeableness, conscientiousness, neuroticism), β/flexibility (extraversion, openness), interpersonal effectiveness (extraversion, agreeableness), and Type D personality (neuroticism, extraversion), followed by additive groupings of traits most commonly reported to be associated with health (neuroticism, conscientiousness, extraversion, openness), may be important to consider in terms of their explanatory power in predicting mortality risk (e.g., Denollet, 2005; Digman, 1997). In other words, it may be that certain combinations of traits may possess greater explanatory power for mortality risk when compared to a model incorporating all five personality traits. This is important as it will help to determine if individual traits predict mortality while adjusting for other traits or whether any relevance to mortality risk is because of the potential relation between traits. This will also allow us to determine if specific groupings of traits are a better fit for predicting mortality risk than others.

Despite decades of research on personality and mortality using longitudinal data and survival analytic techniques, an extensive meta-analysis of the literature on all five traits within a rigorous systematic review framework has yet to be completed. This is important given that personality traits have comparative validity with cognitive ability and socioeconomic status in predicting mortality risk (Roberts et al., 2007). As there is a large variety of research on this topic, it is crucial to use a systematic review framework to capture existing evidence and meta-analytic techniques to estimate overall effects and to examine factors that may moderate the observed associations across studies. In addition, we will also conduct a series of multivariate meta-analyses to determine if individual traits predict mortality risk when adjusting for all other traits. This approach will contribute to estimates of overall effect size and heterogeneity across studies, which will provide a clear understanding of the personality–mortality risk relation.

Method

Transparency and Openness

The data for this review were derived from preexisting published literature and were exempt from the University of Limerick ethics board review. This study design and analytic plan were preregistered, and all meta-analytic data, analysis code, and research materials are available at https://osf.io/f2knr (Johnson, 2021). All reporting in this systematic review and meta-analysis adhered to American Psychological Association (2020a) Journal Article Reporting Standards (Appelbaum et al., 2018) and conformed to standards of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Page et al., 2021). The PRISMA checklist can be found in Supplemental Material S2. All meta-analyses were performed using R Statistical Software v4.3.2 (R Core Team, 2023) using the *metafor* package v4.4-0 (Viechtbauer, 2010), *dmetar* v.1.0 (Harrer et al., 2021), *devtools* v2.4.5 (Wickham et al., 2022), *meta* v6.5-0 (Balduzzi et al., 2019), and *tidyverse* v2.0 (Wickham et al., 2019). A full list of attached R packages, versions, and R scripts can be found in Supplemental Material S1. Amendments to preregistration (see Supplemental Material S3) included four changes to the original plan: to include effect sizes from fully adjusted models instead of unadjusted or base models, a decision not to examine differences in population settings (as the number of clinical studies included was too few for meaningful comparison), to extend the examination of potential moderators of between-study effects, and to conduct a series of multivariate meta-analyses to determine if individual traits were predictive of mortality risk, while adjusting for all other traits, with additional analysis to examine model fit of several groupings of traits as predictors of mortality risk.

Identification and Screening Process

Eligibility Criteria

Studies were included if the following criteria were met.

Study Design. All studies in the current article published effect sizes from longitudinal, observational, and cohort studies that tested personality trait (neuroticism, extraversion, openness, agreeableness, and conscientiousness) associations with all-cause mortality risk as the outcome variable. Effect sizes were included from fully adjusted models, regardless of covariates (Supplemental Table S4), except for studies or models that included self-rated health as a covariate (see Richardson et al., 2019). Studies were excluded if personality traits were treated as a covariate or a confounding variable. Conference presentations, review articles, editorials, or comments and studies using correlational study designs were also excluded.

Publication Status. Studies included were published in the English language, in peer-reviewed journals, as a thesis/dissertation or were unpublished.

Measure of Personality. Included studies needed to use psychological measures of the five-factor personality traits, namely, neuroticism, extraversion, openness, agreeableness, and conscientiousness. The tool used to measure these traits could be measured by, for example, Eysenck's Personality Inventory (H. J. Eysenck & Eysenck, 1964, 1968, 1991) or based on the Five-Factor Model of Personality (Costa & McCrae, 1985, 1989, 1992c; Goldberg, 1992). For conceptual clarity, articles were excluded if they examined aspects of personality within psychiatric disorders or if they solely focused on other aspects of personality (e.g., facets) or transient emotional states (e.g., positive or negative emotionality).

Mortality Data. Included studies needed to report mortality outcomes from longitudinal follow-up data across time and not from cross-sectional reporting of deceased status. Mortality risk had to be measured in terms of all causes. Cause-specific mortality risk was not assessed due to the unreliability of its reporting and the multitude

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of aging-related disease processes involved in longevity estimation (Gerstorf et al., 2006). Due to the nature of such statistical analyses of these types of data, estimates were in the format of hazard ratio (HR), odds ratio, or relative risk. Mortality risk was specifically defined as time to death from baseline assessment to date of death from all causes or censorship for those alive.

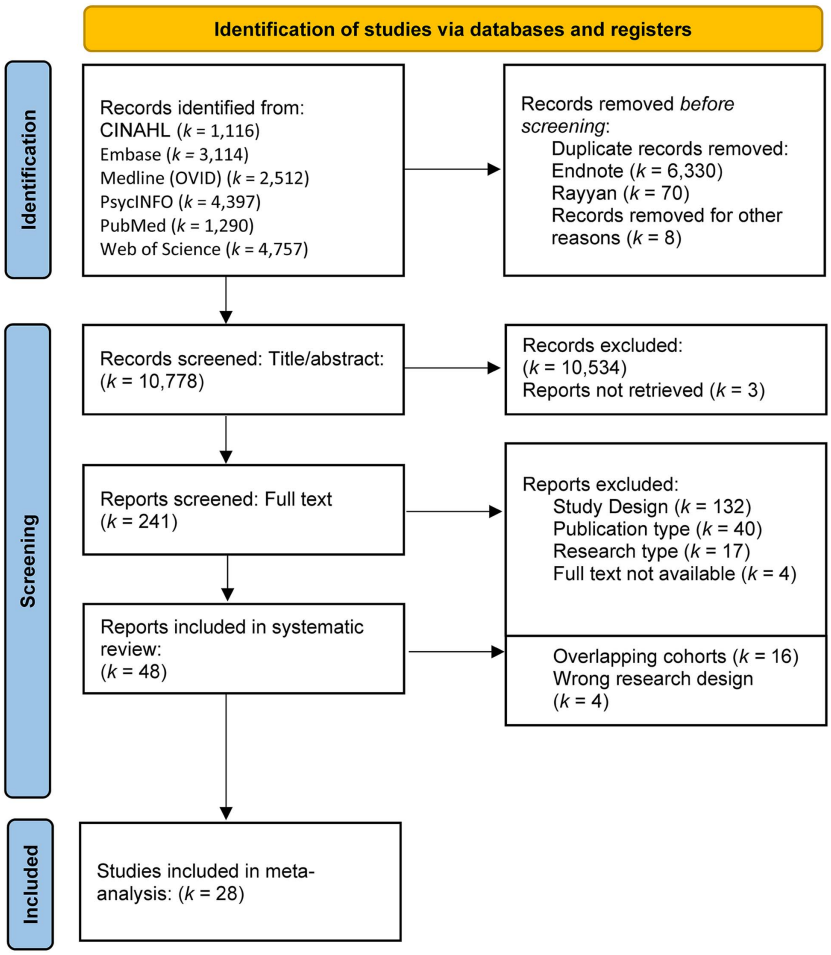
Information Sources, Search Strategy, and Study Selection

A systematic approach to developing a search strategy was adopted (Bramer et al., 2018). Related reviews were consulted for possible approaches to the development of search terms (Kojima et al., 2018; Luchetti et al., 2014; Lui et al., 2022). Following the development of appropriate terms, a review specialist librarian was consulted. The specialist librarian provided initial and ongoing support in conducting the review to the most rigorous standard possible. An example of search terms can be seen below. The full search strategies for each database are listed in Supplemental Table S1, and a PRISMA flowchart is presented in Figure 1.

The search terms used were *personality/ or personality.ab,ti. or extraversion/ or extraversion.ab,ti. or neuroticism/ or neuroticism.ab,ti. or openness.ab,ti. or agreeableness.ab,ti. or conscientiousness.ab,ti or (big five or big 5 or five factor model).ab,ti.*

Figure 1

Preferred Reporting Items for Systematic Reviews and Meta-Analyses Flowchart Outlining Search and Screening Process, Records Included, Excluded, and Reasons for Exclusion



Note. For more information, visit https://www.prismastatement.org. *k* = number of studies; CINAHL = the Cumulative Index to Nursing and Allied Health Literature; OVID = Ovid Platform. Adapted from "The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews," by M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, L. Shamseer, J. M. Tetzlaff, E. A. Akl, S. E. Brennan, R. Chou, J. Glanville, J. M. Grimshaw, A. Hróbjartsson, M. M. Lalu, T. Li, E. W. Loder, E. Mayo-Wilson, S. McDonald, and D. Moher, 2021, *The BMJ*, *372*, Article n71 (https://doi.org/10.1136/bmj.n71). CC BY-4.0. See the online article for the color version of this figure.

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AND *mortality/ or mortality.af. or longevity/ or longevity.af. or death/ or death.af.*

The first search was conducted across six electronic databases covering all years up to the search date (July 2022) including the Cumulative Index to Nursing and Allied Health Literature database, Embase, Medline via the Ovid Platform, APA PsycInfo, PubMed, and Web of Science. A search was conducted to update articles prior to the submission of the article, from July 2022 to September 2, 2024. Several societies were contacted to circulate a request for unpublished data (Supplemental Material S4). No data were submitted following this call.

Search results were exported to EndNote X20, where duplicates were removed. All articles were transferred to the Rayann software program (Ouzzani et al., 2016), where additional duplicates were removed. All titles and abstracts were screened for eligibility by the first author (MMcG), and 10% were screened by a research assistant (MM). If the relevance of the study was ambiguous, full texts were obtained ($k = 241$). Full texts of the remaining studies were assessed by the first author (MMcG), and 12% were assessed by a second reviewer (EK). Discrepancies ($K = .936$) were discussed and resolved. Two published study authors were contacted via email when there was insufficient information to ascertain eligibility. One author responded but was unable to provide the information required, and the other author did not respond.

Overall, 48 studies fulfilled inclusion criteria for the systematic review. Studies were subsequently excluded from the meta-analyses due to overlapping data sets ($k = 16$) or because the research design did not meet inclusion criteria ($k = 4$). Exclusion due to overlapping data sets was done to maintain independence of effect sizes within the meta-analysis, and there were more recent studies with longer follow-up periods, which supplied more information. Not all available data effects were included for Graham et al. (2017) or Turiano et al. (2020) because longer follow-up periods were available (see the Method section).

The aim was to maintain the independence of observations in the final statistical model. In most cases, one effect size was included per study for the meta-analyses; however, there were some exceptions. To ensure the independence of effect sizes and the inclusion of the most meaningful effect sizes, studies were evaluated to identify articles that utilized the same data sets/samples (Strickhouser et al., 2017). A decision rule was used such that studies with the longest follow-up, with the largest sample, and reporting the most personality traits were included. Only one observation was included for each personality trait within an individual study. Where the study with the longest follow-up reported on, for example, two personality traits, then another study may be included for the missing three traits rather than exclude that article. Two studies reported results stratified by sex but included separate sample characteristics, allowing effect sizes to be deemed independent (Supplemental Table S2).

Data Extraction and Coding

A data extraction form, adapted from a Cochrane Collaboration template, was created in Excel (Sambunjak et al., 2017). Relevant demographic characteristics, moderator variables, and the respective effect sizes from each study that met inclusion criteria for the meta-analysis were coded by the first author (MMcG), and 20% of records were verified by a second reviewer (EK). Both coders had perfect interrater reliability; that is, they had 100% agreement on all the coded numbers and characteristics. Effect sizes were chosen from fully adjusted models, indexing the size of the relationship between each of the five personality traits and mortality risk, and extracted directly from published results. Most studies reported effect sizes as HRs. A positive HR, that is, greater than 1.00, indicated an increased mortality risk. Conversely, a negative HR, that is, less than 1.00, indicated a decreased mortality risk (Cox, 1972; Sedgwick & Joekes, 2015). Most articles reported personality traits as continuous variables, whereas others reported relationships between categories of personality traits and mortality risk. The most conservative categories and associated demographic data were used, that is, the lowest category of tertiles rather than the middle or highest. It was decided not to use the average of multiple categories, as it would not have been meaningful. The present study matched the sample size and demographics with the appropriate category from relevant studies.

The study identifier used for the analysis was the study-level first author surname. To calculate the total person-years, we multiplied the study-level number of participants (i.e., not individual participant data) by the number of follow-up years and summed all scores.

$$\text{person-years} = (\text{study a sample size} \times \text{follow-up years}) + (\text{study b sample size} \times \text{follow-up years}). \quad (1)$$

The deceased participants were coded as a percentage of deaths for the sample. Studies with independent effects stratified by males and females were coded (a) and (b). Where one study included more than one panel study but reported effects for panel studies separately, the study ID was coded alphabetically according to the study. The final set of studies was coded along several variables to enable moderation analyses (subgroup and meta-regression). Details on coding categories are provided below, and a data set codebook is available in Supplemental Material S5.

Study-Level Characteristics

Mean age was treated as a continuous variable. Participants were also categorized as "younger adults" (<65 years of age) and "older adults" (>65 years) based on the sample mean age. This is a broad definition as the individual ages within each study had a wide range. Sex was coded as % female. Geographical location was coded as either (a) United Kingdom and Europe, (b) United States of America and Canada, (c) Australia, or (d) Japan. Personality measures were coded as either Eysenck Inventories or Five-Factor Models (Table 1). Studies were coded based on whether adjusted models controlled for any of the other Big Five traits (yes = 1, no = 0). The median number of covariates was 7, so the number of included covariates less than 7 was coded as 0, and covariates equal to or greater than 7 were coded as 1. Health-related factors were coded based on whether a study included certain types of covariates or not (yes = 1, no = 0). The covariates of interest were depression or depressive symptoms (at least one); health behaviors, for example, smoking (at least one); a biological marker, for example, body mass index (BMI); or comorbidity (at least one), for example, cardiovascular disease. Because of differences in how personality traits were scored, that is, as continuous or categorical outcomes in personality traits, studies with categorical variables ($k = 8$, $j = 9$) were coded as 1, and continuous variables were coded as 0. Furthermore, some studies

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Table 1
Characteristics of Studies Included in the Meta-Analysis

Study	Data source	Trait included	Trait scale	Country	Follow-up (year)	*N* sample	*n* deceased (%)	Female (%)	Age *M* (*SD*)
André et al. (2014)	Population study of women Gothenburg	NE	EPI (H. J. Eysenck, 1958)	Sweden	40	589	362 (61)	100	47.20 (NR)
Batty et al. (2016)	Whitehall Study	NE	EPQ (H. J. Eysenck, 1958)	United Kingdom	42	832	781 (94)	0	NR
Bratt et al. (2016)	The Swedish National Study of Aging and Care–Blekinge	NC	NEO-FFI (Swedish version; Costa & McCrae, 1989)	Sweden	12	976	732 (75)	58.3	76.68 (1.19)
Chapman and Elliot (2019)	General Social Survey	NEOAC	BFI-10 (Rammstedt & John, 2007)	United States	8	1,461	170 (12)	52.8	45.80 (16.10)
Christensen et al. (2002)	Primary longitudinal cohort	NEOAC	NEO-FFI (Costa & McCrae, 1992c)	United States	6	174	49 (28)	42.5	54.42 (9.03)
Fry and Debats (2009)	Primary observational cohort	NEOAC	NEO-FFI (Costa & McCrae, 1992c)	Canada	7	450	138 (4)	58	NR
Gale et al. (2017)	U.K. Biobank	N	EPQ-R Short Form (S. B. G. Eysenck et al., 1985)	United Kingdom	9	321,456	4,497 (1)	54	56.17 (8.04)
Graham et al. (2017)$_a$	Einstein Aging Study (EAS)	EOA	IPIP (2002; Goldberg, 1992; Saucier, 1994)	United States	5	1,530	150 (10)	59	81.49 (5.24)
Graham et al. (2017)$_b$	Long Beach Longitudinal Study (LBLS)	EOA	NEO-PI (1994; Costa & McCrae, 1992c)	United States	16	348	159 (46)	52	69.34 (13.83)
Graham et al. (2017)$_c$	The Minority Aging Research Study (MARS)	N	NEO-PI (2004; Costa & McCrae, 1992c)	United States	6	632	88 (14)	24	73.29 (6.45)
Graham et al. (2017)$_d$	The Religious Orders Study (ROS)	EOA	NEO-PI (1994; Costa & McCrae, 1992c)	United States	16	1,185	666 (56)	3	75.66 (7.45)
Graham et al. (2017)$_e$	The Seattle Longitudinal Study (SLS)	EOA	NEO-PI (2001; Costa & McCrae, 1992c)	United States	9	1,331	377 (28)	55	63.40 (15.64)
Graham et al. (2017)$_f$	National Survey of Health and Development (NSHD)	NE	EPI (1972; H. J. Eysenck & Eysenck, 1968)	United Kingdom	38	3,398	496 (15)	48	26.00 (0)
Graham et al. (2017)$_g$	The Octogenarian Twin Study	NE	EPI (1991; H. J. Eysenck & Eysenck, 1968)	Sweden	19	653	650 (99.54)	67	83.58 (3.17)
Graham et al. (2017)$_h$	Swedish Adoption Twin Study of Aging (SATSA)	NEOAC	EPI/NEO (1984; Costa & McCrae, 1992c; H. J. Eysenck & Eysenck, 1968)	Sweden	26	991	649 (65.49)	59	6.00 (13.95)
Graham et al. (2017)$_i$	Longitudinal Study of Amsterdam (LASA)	N	DPQ (1992/93; Luteijn et al., 2000)	Netherlands	17	4,057	2,446 (6.29)	52	68.13 (9.05)
Graham et al. (2017)$_j$	Canberra Longitudinal Study (CLS)	NE	EPQ (1990; H. J. Eysenck & Eysenck, 1968)	Australia	20	894	686 (76.73)	49	76.55 (4.94)
Hagger-Johnson, Roberts, et al. (2012)	U.K. Health and Lifestyle Survey	NE	EPI (H. J. Eysenck & Eysenck, 1964)	United Kingdom	25	5,450	1,699 (31.17)	54	46.17 (17.01)
Hagger-Johnson, Sabia, et al. (2012)	Whitehall II Study (1985–1988)	C	Two items (Hagger-Johnson, Sabia, et al., 2012)	United Kingdom	19	6,800	468 (6.88)	NR	NR
Iwasa et al. (2022)	Longitudinal Interdisciplinary Study on Aging (Tokyo)	NEOAC	NEO-FFI (Japanese version; Costa & McCrae, 1992c; Shimonaka et al., 1997)	Japan	15	1,227	502 (4.91)	NR	NR
Jackson et al. (2015)$_a$	Kelly/Connolly Longitudinal Study on Personality and Newly Formed Marriages	NEOAC	Peer ratings: Trait Personality Rating Scale (36 items; Kelly, 1940)	United States	75	300	293 (97.67)	0	24.80 (3.50)

(*table continues*)

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Table 1 (*continued*)

Study	Data source	Trait included	Trait scale	Country	Follow-up (year)	*N* sample	*n* deceased (%)	Female (%)	Age *M* (*SD*)
Jackson et al. (2015)$_b$	Kelly/Connolly Longitudinal Study on Personality and Newly Formed Marriages	NEOAC	As above	United States	75	300	279 (93.00)	100	24.80 (3.50)
Jokela et al. (2020)$_a$	British Household Panel Survey (BHPS)	NEOAC	BFI (John et al., 1991)	United Kingdom	4	13,780	288 (2.09)	55	45.50 (18.40)
Jokela et al. (2020)$_b$	The English Longitudinal Study of Ageing (ELSA)	NEOAC	MIDUS-PI (26 items; Brim et al., 2020; Lachman & Weaver, 1997)	United Kingdom	2	7,644	109 (1.43)	55	65.90 (9.20)
Jokela et al. (2020)$_c$	Health and Retirement Study (HRS)	EOA	MIDUS-PI (26 items; Brim et al., 2020; Lachman & Weaver, 1997)	United States	9	13,897	2,726 (19.62)	59	68.20 (1.50)
Jokela et al. (2020)$_d$	Midlife Development in the United States (MIDUS)	EOA	MIDUS-PI (25 items; Brim et al., 2020; Lachman & Weaver, 1997)	United States	20	6,259	1.082 (17.29)	52	46.80 (12.90)
Jokela et al. (2020)$_e$	National Child Development Study (NCDS)	NEOAC	IPIP (Goldberg, 1992)	United Kingdom	6	7,092	73 (1.03)	51	5.30 (.40)
Jokela et al. (2020)$_f$	U.K. Household Longitudinal Survey (UKHLS)	OAC	BFI (John et al., 1991).	United Kingdom	4	40,373	557 (1.38)	56	47.20 (18.00)
Jokela et al. (2020)$_g$	Wisconsin Longitudinal Study, Graduate Sample (WLS_G)	EOA	BFI (29 items; John et al., 1991).	United States	22	6,668	1,055 (15.82)	54	54.10 (.50)
Jokela et al. (2020)$_h$	Wisconsin Longitudinal Study, Sibling Sample (WLS_S)	EOA	BFI (29 items; John et al., 1991)	United States	21	3,961	712 (17.98)	53	53.10 (7.30)
Jokela et al. (2020)$_i$	The German Socio-Economic Panel Study (GSOEP)	NEOAC	BFI (15 items; John et al., 1991)	Germany	9	20,431	1,171 (5.73)	52	47.10 (17.50)
Jokela et al. (2020)$_j$	Household, Income and Labour Dynamics in Australia (HILDA) Survey	NEOAC	Personality inventory (36-item) based on Saucier's and Goldberg's Big Five Markers Scale (Goldberg, 1992; Saucier, 1994)	Australia	10	11,090	632 (5.70)	53	43.80 (17.90)
Jonassaint et al. (2007)	Primary study	O	NEO-PI (180 items; Costa & McCrae, 1985)	United States	17	935	463 (49.52)	25	59.80 (9.30)
Mosing et al. (2012)	Australian Twin Study	NE	EPQ-R (short version; S. B. G. Eysenck et al., 1985)	Australia	17	3,752	781 (2.82)	69	61.30 (8.90)
Mroczek et al. (2009)	The Veteran Affairs Normative Aging Study (NAS)	N	EPI-Q (H. J. Eysenck & Eysenck, 1968; Floderus, 1974)	United States	30	1,788	665 (37.19)	0	51.15 (9.34)
Nakaya et al. (2005)	Miyagi Cohort Study	NE	EPQ-R (48 items—dichotomized responses; H. J. Eysenck, 1975, 1991)	Japan	11	823	356 (43.26)	NR	NR
Nakaya et al. (2006)	Glostrup Population Studies	NE	EPI-Q (18 items; H. J. Eysenck, 1967; Eysenck & Eysenck, 1968; Floderus, 1974)	Denmark	26	189	82 (43.39)	66	NR
O'Súilleabháin and Hughes (2018)	The Berlin Aging Study (BASE)	NEO	NEO-PI (Costa & McCrae, 1985)	Germany	19	417	388 (93.05)	46	84.55 (8.62)
Otonari et al. (2021)$_a$	Kyushu University Fukuoka Cohort Study on lifestyle-related diseases	NE	Eight questions (five for neuroticism, three for extraversion; Imai & Nakachi, 1990)	Japan	9	6,559	151 (2.30)	100	62.10 (6.70)

(*table continues*)

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Table 1 (*continued*)

Study	Data source	Trait included	Trait scale	Country	Follow-up (year)	*N* sample	*n* deceased (%)	Female (%)	Age *M* (*SD*)
Otonari et al. (2021)$_b$	Kyushu University Fukuoka Cohort Study on lifestyle-related diseases	NE	As above	Japan	9	4,995	326 (6.53)	0	62.60 (6.80)
Rizzuto et al. (2017)	Swedish National Study of Aging and Care (SNAC_K)	NEO	NEO-FFI (36 items, Swedish version; Costa & McCrae, 1992c)	Sweden	11	2,298	608 (26.46)	61	72.00 (8.62)
Taylor et al. (2009)	Edinburgh Artery Study	NEOAC	NEO-FFI (60 items; Costa & McCrae, 1992c)	United Kingdom	10	1,322	407 (3.79)	6	69.50 (5.60)
Terracciano et al. (2008)	Baltimore Longitudinal Study of Aging (BLSA)	NC	Guildford Zimmerman Scale (300 items, 30 for each of 10 scales; McGuire et al., 1976)	United States	39	2,359	943 (39.97)	38	5.01 (16.90)
Turiano et al. (2020)$_a$	Einstein Aging Study (EAS)	NC	IPIP-50 (Goldberg, 1992; Saucier, 1994)	United States	11	474	128 (27.00)	59	78.98 (5.21)
Turiano et al. (2020)$_b$	The Health and Retirement Study (HRS)	NC	MIDI (Lachman & Weaver, 1997)	United States	9	19,211	3,066 (15.96)	59	66.26 (11.16)
Turiano et al. (2020)$_c$	The Lothian Birth Cohort 1936 (LBC1936)	NC	IPIP (Goldberg, 1992; Saucier, 1994)	United Kingdom	14	962	218 (22.66)	51	69.50 (.84)
Turiano et al. (2020)$_d$	Long Beach Longitudinal Study (LBLS)	NC	NEO-PI-R (Costa & McCrae, 1992c)	United States	19	898	131 (14.59)	56	64.81 (13.19)
Turiano et al. (2020)$_e$	The Sydney Memory and Ageing Study (MAS)	NC	NEO-PI-R (Costa & McCrae, 1992c)	Australia	8	879	180 (2.48)	46	78.71 (4.78)
Turiano et al. (2020)$_f$	The Midlife in the United States (MIDUS; 1995–1996)	NC	MIDI (Lachman & Weaver, 1997)	United States	21	6,245	1,069 (17.12)	53	46.84 (12.91)
Turiano et al. (2020)$_g$	The Veteran Affairs Normative Aging Study (NAS)	C	IPIP (Goldberg, 1992; Saucier, 1994)	United States	27	992	659 (66.43)	0	64.57 (7.46)
Turiano et al. (2020)$_h$	The Older Australian Twins Study (OATS)	NC	NEO-PI-R (Costa & McCrae, 1992c)	Australia	10	534	56 (1.49)	65	71.40 (5.55)
Turiano et al. (2020)$_i$	The Religious Orders Study (ROS)	NC	NEO-FFI (Costa & McCrae, 1992c)	United States	24	1,394	792 (56.81)	71	75.95 (7.47)
Turiano et al. (2020)$_j$	The Seattle Longitudinal Study (SLS)	NC	NEO-PI-R (Costa & McCrae, 1992c)	United States	16	1,649	444 (26.93)	55	64.75 (15.77)
Turiano et al. (2020)$_k$	The Wisconsin Longitudinal Study—Graduates and Sibs (WLS)	NC	BFI (John & Srivastava, 1999)	United States	22	10,711	1,777 (16.59)	54	53.76 (4.52)
Weiss et al. (2020)	Western Electric Study	NEOA	Nine factor scales (Costa & McCrae, 1985; Costa et al., 1985, 1986; Hathaway & McKinley, 1943)	United States	45	1,862	1,693 (9.92)	NR	47.27 (4.32)
Weiss et al. (2013)	The Vietnam Experience Study Cohort	N	MMPI (Costa et al., 1986; Costa & McCrae, 1985; Hathaway & McKinley, 1943)	United States	15	4,270	237 (5.55)	0	37.90 (2.50)
R. S. Wilson et al. (2005)	Chicago Health and Aging Project	NE	NEO-FFI (Costa & McCrae, 1992c)	United States	10	6,158	2,430 (39.46)	6.7	75.00 (7.20)
Yoneda, Graham, et al. (2023)	Rush Memory and Aging Project	NEC	NEO-FFI (Costa & McCrae, 1992c)	United States	23	1,954	1,059 (54.20)	74	79.93 (7.57)

Note. Subscript letters a–k indicate separate data sources within a study. Jackson et al. (2015), Otonari et al. (2021) = males; Jackson et al. (2015), Otonari et al. (2021) = females. N = neuroticism; E = extraversion; O = openness; A = agreeableness; C = conscientiousness; EPI/EPQ = Eysenck Personality Inventory/Questionnaire [-R = Revised; -Q = abbreviated versions]; NR = not reported; NEO-FFI = NEO Five-Factor Inventory (60 items); BFI = Big-Five Inventory; IPIP = International Personality Item Pool; NEO-PI = NEO Personality Inventory; DPQ = Dutch Personality Questionnaire; MIDUS-PI = Personality Inventory from the Midlife in the United States survey; MIDI = The Midlife Development Inventory; MMPI = Minnesota Multiphasic Personality Inventory; follow-up years = maximum follow-up time; NEO = Neuroticism, Extraversion, and Openness.

reported effect sizes based on a nonstandardized score (e.g., a 1-point or unit increase on a scale), while others reported effect sizes based on a standardized score (e.g., a one standard deviation increase or converting to *z* scores). Nonstandardized scores were coded as 0, and standardized scores were coded as 1. As nonstandardized scores varied in scale and units, a further sensitivity analysis was performed to find out if this affected the main outcome.

For the meta-analysis, higher scores of a personality trait represented increased levels of that trait. In conducting the meta-analysis in R, some effect sizes needed to be reversed due to inconsistencies in the direction of effects for some variables; for example, high scores on "emotional stability" represented low neuroticism in some studies (Supplemental Table S3 lists all studies with reversed effects). To facilitate interpretation, effect sizes were converted in the same direction and to a common metric (logHRs) and standard error (*SE*) in Microsoft Excel and combined using a random-effects model using the "metafor" package in R (Tierney et al., 2023; Viechtbauer, 2010). These were transformed back into HRs and confidence intervals for ease of interpretation within the R program.

Meta-Analytic Procedure

Random-effects meta-analyses were used to pool effect sizes, with study as a stratifying variable because considerable between-study heterogeneity was anticipated. A separate meta-analysis was run for each personality trait individually because we follow the approach that personality traits are inherently different, and many of the effect sizes also control for other personality traits. The inverse-variance method was used (Higgins et al., 2009), with maximum likelihood applied for τ^2 variance estimation (Turiano et al., 2015; Viechtbauer, 2005) and the Q-Profile method for confidence interval of τ^2 and τ. The Hartung–Knapp adjustment for the random-effects model was used (Knapp & Hartung, 2003; Sidik & Jonkman, 2002).

The *metafor* program performed the generic inverse-variance meta-analysis, which assigned weights to each study based on the inverse of the variance of the effect estimate (Viechtbauer, 2010). Therefore, studies with higher precision (i.e., a smaller *SE*) were given greater weight (Deeks et al., 2023; Hedges & Olkin, 2014). The I^2 statistic (Higgins & Thompson, 2002) was used to quantify between-study heterogeneity. This represented the percentage of variability in the effect sizes not caused by sampling error (Harrer et al., 2021). I^2 was calculated by the *meta* package in R (Balduzzi et al., 2019). Where $I^2 = 25\%$, there was low heterogeneity, compared with $I^2 = 50\%$, which indicated moderate heterogeneity, and $I^2 = 75\%$ indicated substantial heterogeneity (Higgins & Thompson, 2002). However, as the value of I^2 depended on the precision of included studies (Borenstein et al., 2017), we also reported Cochran's *Q* statistic (Cochran, 1954). Tau-squared, or τ^2, represented the estimate of the variance of the distribution of true effect sizes. While it is less sensitive to the number and precision of included studies, it is more difficult to interpret the practical relevance (Harrer et al., 2021). This limitation was overcome by using the prediction interval (IntHout et al., 2016).

The prediction interval, calculated based on the *t* distribution, predicted a range of effects into which the effects of future studies can be expected to fall, given the present evidence (IntHout et al., 2016). If the prediction interval did not cross one, this meant that even if there were mixed effects, this would be the range of effects that could be expected in future studies across various contexts and populations, and if the prediction interval crosses one, future predictions are less sure (IntHout et al., 2016).

Sensitivity analyses were conducted for each personality trait to identify outliers, and meta-analyses were conducted removing outlier effects. The effect of a study was considered an outlier using two different approaches. First, outliers were identified if their confidence interval did not overlap with the confidence interval of the pooled effect as implemented using the "find.outliers" function in the "dmetar" package (Harrer et al., 2021). Second, we examined influential case detection based on Cook's distance using the threshold of $4/n$ (n = number of observations; Arimie et al., 2020).

Moderator Analyses

A series of subgroup analyses and meta-regressions were conducted to identify the presence and extent of statistical heterogeneity, specifically to explore if effects of personality traits on mortality risk varied based on study-level factors: age, sex, and geographical location (United Kingdom and Europe, North America, Australia, Japan). In exploratory analyses, we examined other potential causes of heterogeneity; these included differences based on whether studies controlled for the other personality traits, differences based on continuous or categorical scoring of personality traits, and the personality measure, based on Eysenck Personality Inventories (e.g., H. J. Eysenck & Eysenck, 1968, 1975) or inventories capturing the Five-Factor Model (Costa & McCrae, 1992c). We also checked for between-study differences based on whether the study included specific covariates or not. The covariates of interest were depression, or depressive symptoms; at least one health behavior, for example, smoking, physical inactivity, or alcohol use; at least one biological marker, for example, BMI; and at least one comorbidity, for example, cardiovascular disease or diabetes. R^2 represents the amount of variance accounted for by the moderator.

Publication Bias

Publication bias was assessed using multiple methods, visually using funnel plots (Supplemental Material S6) and statistically for small-study bias using Egger's test (Egger et al., 1997). Duval and Tweedie's (2000) trim and fill method was used to adjust for funnel plot asymmetry and impute "missing" effects. The pooled effect size of the "extended" data set then represented the estimate when correcting for small-study effects (Schwarzer et al., 2015). We also supplemented the trim and fill method with the inclusion of the Precision-Effect Test and Precision-Effect Estimate with Standard Error (PET–PEESE) approach, which determines if there is evidence of publication bias while estimating a true effect size corrected for bias (Stanley & Doucouliagos, 2014). Following the decision rule proposed by Stanley and Doucouliagos (2014), we reported the PET estimate when the PET intercept was not statistically significant, indicative of no true effect beyond sampling error, and the PEESE estimate when the PET intercept was significant in order to provide a more accurate estimate accounting for small-study bias, assuming a true effect does in fact exist. It must be noted that these approaches are not without their limitations (e.g., Carter et al., 2019; Simonsohn et al., 2014; Stanley, 2017).

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Quality Assessment

Study quality was evaluated according to the criteria of the National Institutes of Health Quality Assessment Tool for Observational Cohort and Cross-sectional Studies (https://www.nhlbi.nih.gov/health-topics/study-quality-assessment-tools; Supplemental Material S7). This is a well-known and established tool for assessing methodological quality. Quality ratings were based on a qualitative judgement checklist (yes/no/cannot determine/not reported/not applicable), with an overall assessment of quality rating as "good," "fair," or "poor." In general, a "good" study had the least risk of bias, and results were deemed robust. Sample questions included "Was the study population clearly specified and defined?" and "Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?" Studies were assessed in terms of quality, with quality ratings assigned based on guidelines. These were then checked independently by two raters (MMcG and JK), and any disagreements were resolved through discussion, reaching 100% consensus on all studies.

Multivariate Meta-Analyses

We set out to determine if specific traits predicted mortality risk when all other traits were adjusted for. We also examined the model fit of specific trait groupings. To conduct a series of multivariate meta-analyses, we converted all HRs to biserial correlations (r). Extraction of correlations between personality traits from each study was attempted. However, given the very high frequency of nonreporting in studies, it was not possible to utilize correlations from the specific studies included. To overcome this, we took several approaches. We extracted personality trait correlations from a large comprehensive review that reported this information (Buecker et al., 2020). While these estimates stem from very comprehensive data, we also ran sensitivity checks to ensure that findings did not change at other varying levels ($r = .3$, $r = .5$, $r = .7$). Using proxy measures of correlations for these purposes is a common practice (Jackson et al., 2011).

Results

The PRISMA flowchart outlines the literature search, screening process, and the number of records included in the meta-analytic review (Figure 1). The total sample is represented by N, and n represents a subsample of cases. The number of studies is represented by k, and the number of independent effects is represented by j (American Psychological Association, 2020b). The meta-analytic review included study-level data from 28 studies, with a total of 158 independent effect sizes. The studies were published from 2002 to 2024 and varied by personality trait: neuroticism ($j = 46$, $n = 475{,}263$, 53% female), extraversion ($j = 36$, $n = 131{,}999$, 54% female), openness ($j = 25$, $n = 145{,}722$, 54% female), agreeableness ($j = 22$, $n = 142{,}534$, 54% female), and conscientiousness ($j = 29$, $n = 161{,}719$, 52% female; Table 1). Three meta-analytic studies reporting on data from ongoing panel studies yielded 2,025,882 person-years of data, with a further 3,952,113 person-years of data stemming from additional empirical studies. Population samples were from the United Kingdom and Europe—Sweden, Denmark, and Germany ($n = 439{,}710$)—the United States of America and Canada ($n = 99{,}396$), Australia ($n = 17{,}149$), and Japan ($n = 13{,}604$). Overall, the meta-analyses included $N = 569{,}859$ participants (N_{range} = 174–321,456, 53% female). The duration from the start of the earliest data collection period to the end dates of data collection in these studies (1935–2017) yielded 82 years (N_{range} 2–75 years, $Mdn = 16$ years) of data. The total follow-up time amounted to 5,997,667 person-years.

All studies included age as a covariate. Younger adults (<65 years) made up 60% of the population, while older adults (>65 years) made up 40%. The mean age of the participants was 61. Of the studies that included both sexes, 87% controlled for sex, and 13% did not. Education was included as a covariate in 62% of studies. Only 24% controlled for ethnicity, while 76% did not. Only 19% of studies controlled for socioeconomic status in some form, that is, Townsend index, income, or employment grade; 53% controlled for ≥7 covariates; and 47% controlled for <7 covariates (Supplemental Table S4). Frequencies of other study-level characteristics and covariates are presented in Table 2.

Personality was measured using a variety of instruments (Table 1). Most studies scored personality as a continuous measure; however, some studies used categorical scoring techniques ($k = 8$) by categorizing personality in tertiles ($k = 5$; Batty et al., 2016; Fry & Debats, 2009; Iwasa et al., 2022; Nakaya et al., 2006; Otonari et al., 2021) or quartiles ($k = 3$; André et al., 2014; Jonassaint et al., 2007; Nakaya et al., 2005; Supplemental Table S5).

Quality Assessment

Overall, the studies included were judged to be of "good" quality. In most cases, the research question was clearly stated and the population clearly specified and defined. Sample size justification is not usually provided in observational panel studies because the analyses are often exploratory in nature. In most cases, however, effect sizes and confidence intervals were given. The outcome mortality data were provided by the National Death Index of the country of study origin in most cases, with mortality information for many data sets collected at annual follow-ups (e.g., Jokela et al., 2020). Some researchers gathered information from a combination of hospital records or data from the Social Security Administration death index (e.g., Christensen et al., 2002). Ascertainment of mortality (in the event of death) in Fry and Debats (2009) was done solely based on reports from the informants' family members. Others had interviews or telephone calls with family members and confirmed deaths through the National Death Index (Terracciano et al., 2008; Turiano et al., 2020). One study did not provide the procedure for documenting deaths as they were described elsewhere (Jonassaint et al., 2007). Some studies may not have had a sufficient timeframe to assess mortality as an outcome, as the percentage of deceased participants was less than 5% (Gale et al., 2017; Jokela et al., 2020; Otonari et al., 2021). It is well established that the percentage of deceased participants is a critically important determinant of power in survival analyses.

Meta-Analytic Results

Neuroticism

Neuroticism ($j = 46$) was associated with an increased mortality risk (HR = 1.03, 95% CI [1.02, 1.04], $t = 5.89$, $p < .001$, prediction interval = 1.00–1.06; see Figure 2). There were small but statistically significant differences between studies ($I^2 = 37\%$), $Q(45) = 71.13$, $p < .01$, $\tau^2 = .001$ (.001–.003), $\tau = .013$ (.001–.051). Egger's

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Table 2
Frequencies of Study-Level Characteristics and Covariates

Personality trait[a]	N (j = 46)	E (j = 36)	O (j = 25)	A (j = 22)	C (j = 29)
Location					
United Kingdom and Europe	18	14	9	7	10
North America	19	15	14	13	15
Australia	5	3	1	1	3
Japan	4	4	1	1	1
Covariates					
Mdn <7	16	16	11	9	7
Mdn ≥7	30	20	14	13	22
Scoring					
Continuous	38	28	22	20	27
Categorical	8	8	3	2	2
Scoring					
Standardized	34	27	24	21	26
Nonstandardized	12	9	1	1	3
Personality measure					
Eysenck Inventories	13	11	0	0	0
Five-Factor Model	33	25	25	22	29
Depression					
Yes	3	2	1	0	28
No	43	34	24	22	1
Biological marker					
Yes	12	9	2	2	4
No	34	27	23	20	25
Comorbidity					
Yes	8	5	3	1	3
No	38	31	22	21	26
Health behavior					
Yes	12	9	2	2	2
No	34	27	23	20	27

Note. j = independent effect sizes.
[a] Traits included: N = neuroticism; E = extraversion; O = openness; A = agreeableness; C = conscientiousness.

test (Table 3) indicated the potential presence of publication bias. Funnel plots are available in Supplemental Material S7. The trim and fill method (Duval & Tweedie, 2000) added 12 studies, and the outcome was slightly attenuated (HR = 1.02, [1.01, 1.03], $t = 3.60$, $p < .001$, prediction interval = .99–1.05), $\tau^2 = .001$ (.001–.006), $I^2 = 49\%$, $\tau = .014$ (.027–.079). The PET model revealed a significant intercept ($\beta = .011$, $SE = .003$, $p < .001$), indicating evidence of a true underlying effect after adjusting for small-study bias. The PEESE model produced a significant intercept ($\beta = .03$, $SE = .005$, $p < .001$; [.019, .039]), suggesting that neuroticism was still associated with increased mortality risk even following adjustment for potential publication bias.

No outlier studies were identified using the influence method. Using the confidence interval approach to identifying outliers (Harrer et al., 2021), several studies were identified (Jackson et al., 2015; Otonari et al., 2021; Weiss et al., 2013; R. S. Wilson et al., 2005). Meta-analysis was conducted with the outliers removed. The exclusion did not substantially change the outcome (HR = 1.03, 95% CI [1.02, 1.04], $t = 6.87$, $p < .001$); however, between-study heterogeneity was reduced ($I^2 = 12\%$), $\tau^2 = .001$ (.001–.001). Removing categorical studies did not substantially change the outcome (HR = 1.03, [1.02, 1.04], $t = 5.48$, $p < .001$, $I^2 = 35.1\%$, $\tau^2 = .001$, $\tau = .012$). Removing other-rated studies (Jackson et al., 2015) also did not change the outcome (HR = 1.03, [1.02, 1.04], $t = 5.83$, $p < .001$, $I^2 = 34\%$, $\tau^2 = .001$, $\tau = .012$). There was a significant difference between studies that used nonstandardized scoring compared to standardized scoring, $Q(1) = 8.01$, $p < .01$. Meta-analysis was conducted with the exclusion of effects based on nonstandardized measures. Studies that used nonstandardized scoring ($j = 12$, HR = 1.01, [1.00, 1.02]) had weaker effects than standardized scoring, and mortality risk was slightly increased when they were excluded ($j = 34$, HR = 1.04, [1.02, 1.05], $t = -5.43$, $p < .001$, prediction interval = 1.00–1.07), but did not explain heterogeneity between studies ($I^2 = 38\%$), $Q(33) = 53.31$, $p = .014$, $\tau^2 = .005$, $\tau = .07$.

Age significantly moderated the effects of neuroticism on mortality risk ($\beta = -.001$, $SE = .001$, $p = .038$), $t(39) = -2.15$, potentially explaining 53% of the variance, such that the effects of neuroticism were stronger for younger populations. A follow-up analysis explored the meta-analytic effect for younger (<65) and older samples (>65) separately. Older adults had an increased mortality risk ($j = 17$, HR = 1.01, 95% CI [1.01, 1.02]). However, the effect of neuroticism on increased mortality risk was stronger for younger adults ($j = 24$, HR = 1.03, [1.02–1.05]). In other moderator analyses, studies that controlled for health behavior, $Q(1) = 6.58$, $p = .01$, or a biological marker, $Q(1) = 8.84$, $p = .003$, or comorbidity, $Q(1) = 4.46$, $p = .035$, had weaker pooled effects but retained significance (Table 4). Studies with missing data were omitted from the model fitting. Nonsignificant results for other variables can be found in Supplemental Material S8.

Extraversion

Higher extraversion ($j = 36$) was associated with decreased mortality risk (HR = .97, 95% CI [.94, .99], $t = -2.87$, $p = .007$,

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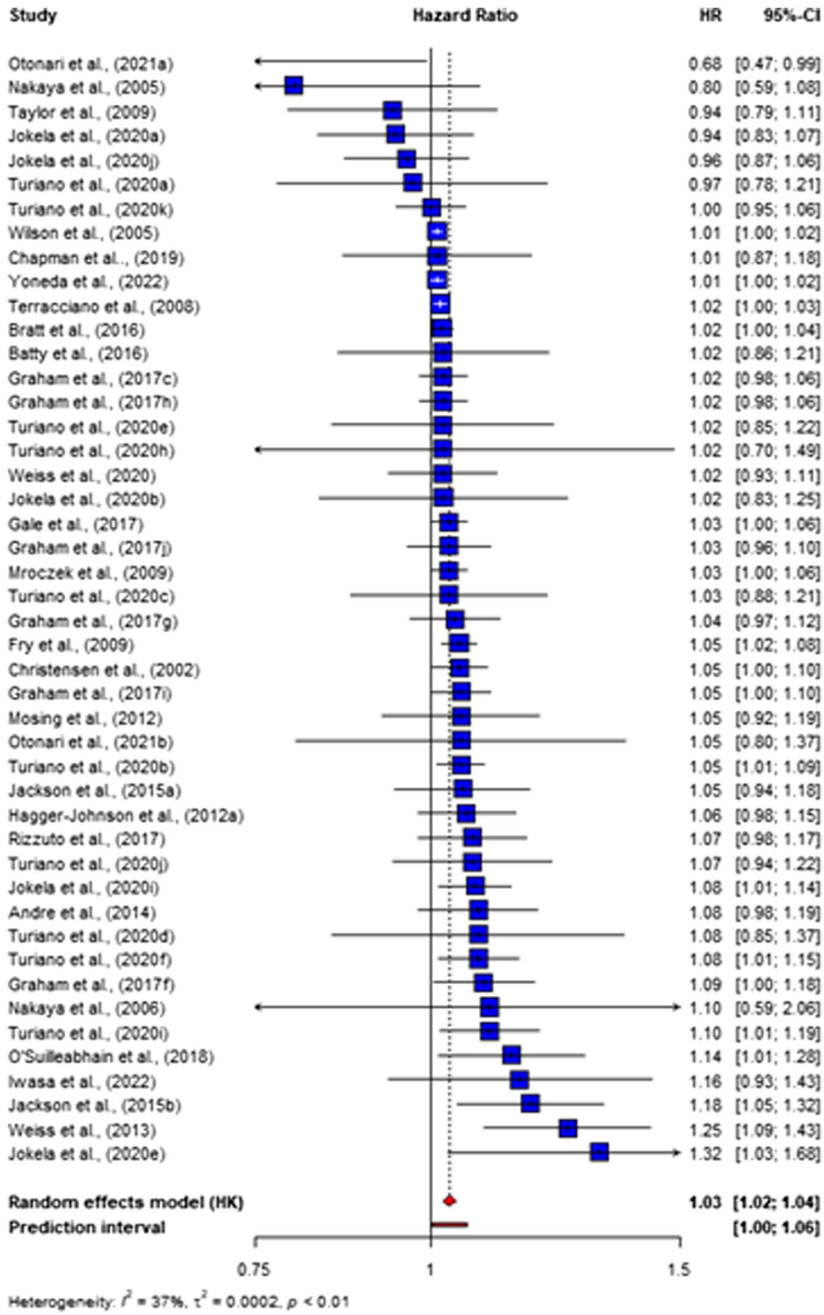
Figure 2

Forest Plot Showing Associations Between Neuroticism and Mortality Risk



Note. The figure shows the forest plot of the random-effects meta-analytical model performed on single effect sizes (HR) aggregated by study. In the figure, effect sizes are transformed from lnHR and standard error to HR and CIs for ease of interpretation. Error bars represent the 95% CIs of the random effects. The summary diamond represents the overall meta-analytical estimate with 95% CI. The red bar represents the range of the prediction interval. Tolerance intervals were calculated using the Hoffman and Kringle (HK) method within a one-way random-effects model (Montes et al., 2019). CI = confidence interval; HR = hazard ratio. See the online article for the color version of this figure.

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Table 3
Egger's Test Results for Personality Traits

Personality trait	Intercept	95% CI	*t*	*p*
Neuroticism	.729	[.33, 1.13]	3.60	**<.001**
Extraversion	−.561	[−1.2, .08]	−1.72	.095
Openness	−.68	[−2.17, .81]	−.897	.379
Agreeableness	−.288	[−.95, 1.53]	.456	.653
Conscientiousness	−2.013	[−3.03, .99]	−3.88	**<.001**

Note. The intercept assesses the potential presence of publication bias. A significant intercept suggests asymmetry in the funnel plot. Significant values appear in bold. CI = confidence interval.

prediction interval = .89–1.06; Figure 3). There were moderate significant between-study differences (I^2 = 63%), $Q(35)$ = 94.04, $p < .001$, $\tau^2 = .002$ (.001–.009), $\tau = .042$ (.031, .097). In assessing publication bias, Egger's test did not indicate the presence of funnel plot asymmetry (Table 3). Using the PET–PEESE approach, there was no evidence of publication bias.

No outlier studies were identified using the influence method. Using the confidence interval approach to identifying outliers (Harrer et al., 2021), several studies were identified (Graham et al., 2017; Jokela et al., 2020). Meta-analysis was conducted with the outliers removed. The results did not substantially change the outcome (HR = .98, [.97–.99], $t = -4.75$, $p < .001$, $\tau^2 = .001$, I^2 = 36%). Removing categorical studies did not substantially change the overall result (HR = .97, [.94–.99], $t = -2.78$, $p < .01$, prediction interval = .88–1.06). Removing other-rated studies (Jackson et al., 2015) also did not change the outcome (HR = .96, [.94–.99], $t = -2.91$, $p < .01$).

In moderator analyses, effect differences for extraversion did vary based on geographical location, $Q(3) = 1.22$, $p = .017$. Extraversion was not associated with mortality in the English, European, or Japanese samples but was associated with decreased mortality in the North American and Australian samples (Table 4). Studies using measures based on the Five-Factor Model were associated with decreased mortality risk, while in contrast, studies using measures based on Eysenck Inventories were not, $Q(1) = 3.98$, $p < .046$. The percentage of deceased participants was a significant contributor, accounting for R^2 = 37% of the variance. Additionally, for every one-unit increase in the percentage of deceased participants, the mortality risk increased by .0008 ($\beta < .001$, $SE = .001$, $p = .042$).

Openness

Openness ($j = 25$) was associated with a decreased mortality risk (HR = .96, 95% CI [.93, .99], $t = -2.55$, $p = .017$, prediction interval = .86–1.07; Figure 4). There were significant moderate differences between studies (I^2 = 58%), $Q(24) = 56.97$, $p < .001$, $\tau^2 = .003$, $\tau = .051$. No publication bias was detected, as Egger's test did not indicate the presence of funnel plot asymmetry (Table 3). Significant effects for openness did not withstand the adjustment for small-study bias (PET–PEESE). The PET intercept was not statistically significant ($p = .24$), indicating no clear evidence of a true effect following adjustment for small-study bias. No influential outlier studies were identified. In identifying outliers using the confidence interval approach (Harrer et al., 2021), one study was identified as an outlier (Jokela et al., 2020). Meta-analysis was conducted with the outlier removed. The results did not substantially change the outcome (HR = .97, [.94–1.00], $t = -2.11$, $p = .046$, $\tau^2 = .002$, I^2 = 49%). Removing categorical studies from the meta-analysis did not change the direction of effects but did render them nonsignificant (HR = .97, [94–1.00], $t = -1.93$, $p = .067$, $\tau^2 = .002$). Removing other-rated effects ($j = 2$) did not substantially change the outcome (HR = .97, [.93–1.00], $t = -2.23$, $p = .036$).

Moderator analysis effects varied significantly based on whether a categorical or continuous effect size was used for openness, $Q(1) =$

Table 4
Summary Moderator Analyses for Personality Traits

Subgroup difference Personality trait	Moderator variable	Category	*j*	HR	95% CI *LL*	95% CI *UL*
Neuroticism	Biological marker	No	34	1.03	1.02	1.05
		Yes	12	1.01	1.00	1.02
	Comorbidity	No	38	1.03	1.02	1.04
		Yes	8	1.01	1.00	1.03
	Health behavior	No	34	1.03	1.02	1.04
		Yes	12	1.01	1.00	1.02
Extraversion	Location	United Kingdom and Europe	14	1.01	.98	1.04
		North America and Canada	15	.95	.92	.98
		Australia	3	.97	.94	1.00
		Japan	4	.96	.69	1.35
	Personality measure	Eysenck Inventories	11	.99	.97	1.02
		Five-Factor Model	25	.96	.93	.98
Openness	Scoring	Categorical	3	.88	.78	1.00
		Continuous	22	.97	.94	1.00
Conscientiousness	Biological marker	No	26	.90	.86	.93
		Yes	4	.97	.94	1.01

Note. "No" indicates the number of effects not controlling for a particular covariate, and "Yes" indicates that the study did control for that covariate. *j* = effect sizes; HR = hazard ratio; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

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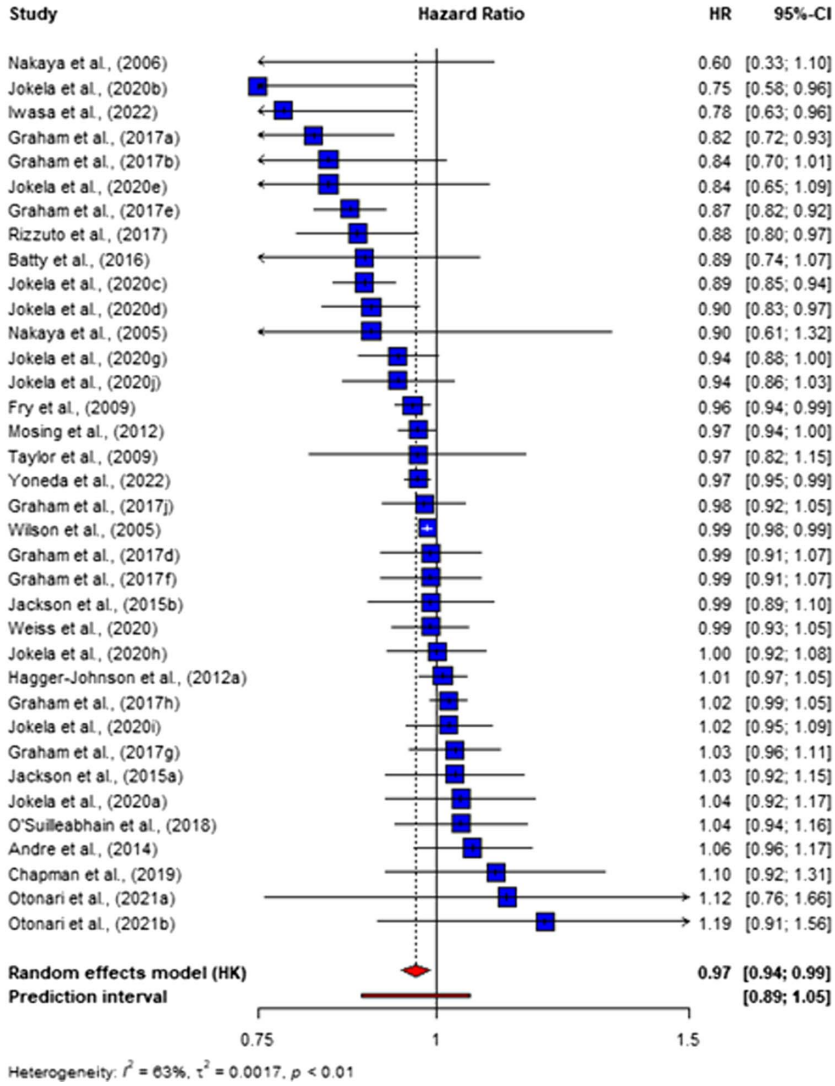
Figure 3

Forest Plot Showing Associations Between Extraversion and Mortality Risk



Note. The figure shows the forest plot of the random-effects meta-analytical model performed on single effect sizes (HR) aggregated by study. In the figure, effect sizes are transformed from lnHR and standard error to HR and CIs for ease of interpretation. Error bars represent the 95% CIs of the random effects. The summary diamond represents the overall meta-analytical estimate with 95% CI. The red bar represents the range of the prediction interval. Tolerance intervals were calculated using the Hoffman and Kringle (HK) method within a one-way random-effects model (Montes et al., 2019). CI = confidence interval; HR = hazard ratio. See the online article for the color version of this figure.

8.58, $p < .01$. Pooled effects based on categorical scoring had stronger effects but less precision, as evidenced in the broader confidence interval (Table 4).

Agreeableness

Higher agreeableness ($j = 22$) was not significantly associated with mortality risk (HR = .98, 95% CI [.95, 1.02], $t = -.92$, $p = .366$, prediction interval = .86–1.12; Figure 5). There were significant moderate differences between studies ($I^2 = 69\%$), $Q(21) = 66.88$, $p < .001$, $\tau^2 = .004$, $\tau = .061$. Publication bias was not detected via Egger's test and the PET–PEESE method. No influential outlier studies were detected. Using the confidence interval approach to identifying outliers (Harrer et al., 2021), a few studies were identified as outliers (Chapman & Elliot, 2019; Jackson et al., 2015; Jokela et al., 2020). Meta-analysis was conducted with the outliers removed. The overall outcome did not change substantially, with pooled effects indicating that agreeableness was not a significant predictor of mortality risk (HR = .99, [.96–1.02], $t = -.62$, $p < .544$, $I^2 = 61\%$, $\tau^2 = .002$, $\tau = .047$).

In moderator analyses, the percentage of deceased participants significantly moderated the effects of agreeableness on mortality

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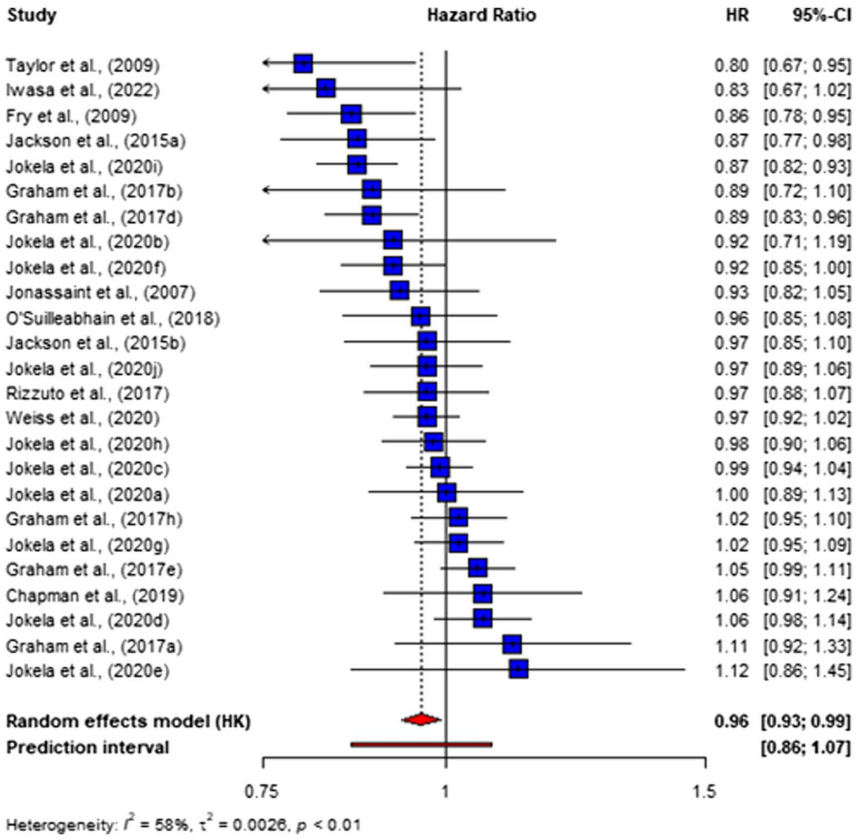
Figure 4

Forest Plot Showing Associations Between Openness and Mortality Risk



Note. The figure shows the forest plot of the random-effects meta-analytical model performed on single effect sizes (HR) aggregated by study. In the figure, effect sizes are transformed from lnHR and standard error to HR and CIs for ease of interpretation. Error bars represent the 95% CIs of the random effects. The summary diamond represents the overall meta-analytical estimate with 95% CI. The red bar represents the range of the prediction interval. Tolerance intervals were calculated using the Hoffman and Kringle (HK) method within a one-way random-effects model (Montes et al., 2019). CI = confidence interval; HR = hazard ratio. See the online article for the color version of this figure.

risk (β = −.002, *SE* = .001, $p < .01$). For every one-unit increase in the percentage of deceased participants in the sample, the mortality risk decreased by .002, accounting for $R^2 = 48\%$ of the variance. Follow-up time was also a significant moderator (β = −.002, *SE* = .001, $p = .017$), such that for every one-unit increase in maximum follow-up time, the mortality rate decreased by .002, accounting for 31% of the variance. Estimated between-study heterogeneity was high with $I^2 = 78\%$ for North American studies, compared with 24% for the United Kingdom and Europe. Australia and Japan had one study each examining agreeableness, which means that the effects for those countries would be underpowered. All measures of agreeableness were based on the Five-Factor Model.

Conscientiousness

Conscientiousness ($j = 29$) was associated with a decreased mortality risk (HR = .90, 95% CI [.87, .94], $t = -5.81$, $p < .001$, prediction interval = .78–1.05; Figure 6). Between-study differences were high ($I^2 = 83\%$), $Q(28) = 164.60$, $p < .001$, $\tau^2 = .005$, $\tau = .07$. Publication bias was detected, as Egger's test indicated the presence of funnel plot asymmetry (Table 3). The trim and fill method (Duval & Tweedie, 2000) added 12 studies. The corrected effect (HR = .97, [.92–1.01], $t = -1.42$, $p = .164$, prediction interval = .74–1.26), while in the same direction as the initial effect, was no longer significant, with high heterogeneity ($I^2 = 88\%$), $Q(40) = 342.90$, $p < .001$, $\tau^2 = .169$. PET–PEESE also detected publication bias. However, significant effects for conscientiousness withstood correction for small study bias.

No influential outliers were observed. In determining outliers using the confidence interval approach (Harrer et al., 2021), several studies were identified (Bratt et al., 2016; Fry & Debats, 2009; Jackson et al., 2015; Terracciano et al., 2008; Turiano et al., 2020; Yoneda, Graham, et al., 2023). Meta-analysis was conducted with the outliers removed. The results did not substantially change the outcome, indicating that conscientiousness was a significant predictor of decreased mortality risk (HR = .90, [.87–.93], $t = -6.25$, $p < .001$) but strengthened the prediction interval (.82–.99). Although removing outliers reduced heterogeneity ($I^2 = 48\%$),

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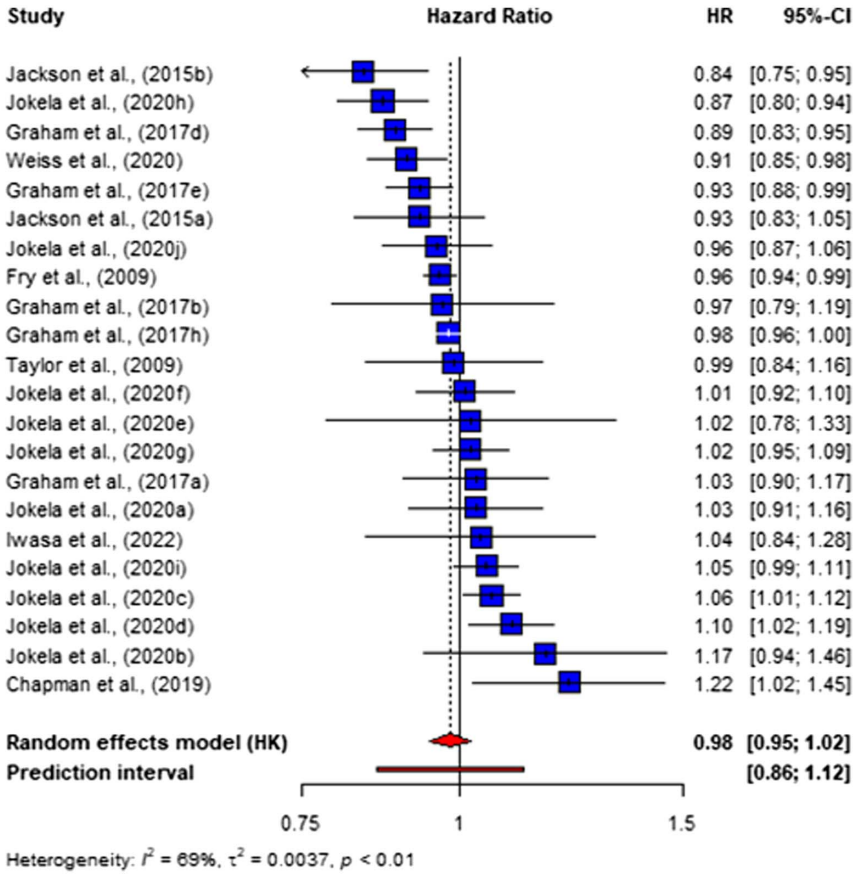
Figure 5

Forest Plot Showing Associations Between Agreeableness and Mortality Risk



Note. The figure shows the forest plot of the random-effects meta-analytical model performed on single effect sizes (HR) aggregated by study. In the figure, effect sizes are transformed from lnHR and standard error to HR and CIs for ease of interpretation. Error bars represent the 95% CIs of the random effects. The summary diamond represents the overall meta-analytical estimate with 95% CI. The red bar represents the range of the prediction interval. Tolerance intervals were calculated using the Hoffman and Kringle (HK) method within a one-way random-effects model (Montes et al., 2019). CI = confidence interval; HR = hazard ratio. See the online article for the color version of this figure.

differences remained significant, $Q(22) = 42.19$, $p < .01$, $\tau^2 = .003$, $\tau = .44$.

The trim and fill method is limited in heterogeneous data sets; therefore, a trim and fill was conducted with outliers excluded ($j = 6$; see above). The corrected effect was nearly identical to the pooled effect (HR = .91, [.88–.95], $t = -4.97$, $p < .001$, prediction interval = .81–1.02). However, heterogeneity was reduced ($I^2 = 54\%$, $\tau^2 = .003$, $\tau = .05$).

Removing categorical studies from the meta-analysis did not substantially change the outcome (HR = .90, [.87–.94], $t = -5.72$, $p < .001$, prediction interval = .78–1.05, $I^2 = 83\%$, $\tau^2 = .004$, $\tau = .066$). Removing other-rated studies (Jackson et al., 2015) also did not substantially change the outcome (HR = .91, [.88–.94], $t = -5.66$, $p < .001$). Excluding effects based on nonstandardized measures (Bratt et al., 2016; Christensen et al., 2002; Iwasa et al., 2022) also did not change the outcome (HR = .90, [.87–.94], $t = -5.77$, $p < .001$) and did not explain high heterogeneity between studies ($I^2 = 83\%$), $\tau^2 =$ .005 (.002–.012), $\tau = .069$, prediction interval = .78–1.04. In moderator analysis, the inclusion of a biological marker as a covariate ($j = 4$), for example, BMI, attenuated the effect of conscientiousness on mortality to nonsignificance, $Q(1) = 14.58$, $p < .001$ (Table 4).

The multivariate meta-analysis found that effect estimates for neuroticism, extraversion, and conscientiousness remained significant following the adjustment of all personality traits (Table 5). Openness was no longer significant ($p = .137$). To check the robustness of these associations and to ensure that estimates were robust to alternative trait-trait correlation coefficients (Table 6), sensitivity checks were conducted. Multivariate analyses were repeated with correlations between traits set at varying levels ($r = .3$, $r = .5$, $r = .7$). Results remained unchanged. We also examined if results were consistent when using cluster robust variance estimation as a sensitivity approach to adjust the *SE* and confidence interval to account for the dependent data structure. Results remained unchanged.

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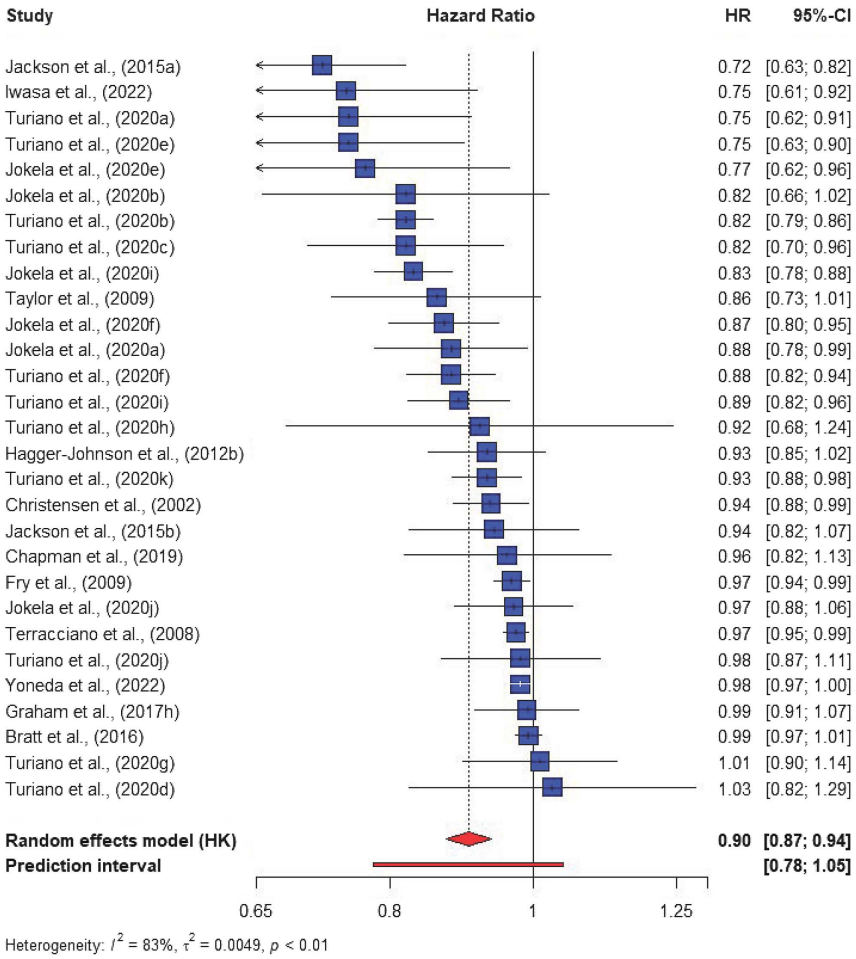
Figure 6

Forest Plot Showing Associations Between Conscientiousness and Mortality Risk



Note. The figure shows the forest plot of the random-effects meta-analytical model performed on single effect sizes (HR) aggregated by study. In the figure, effect sizes are transformed from lnHR and standard error to HR and CIs for ease of interpretation. Error bars represent the 95% CIs of the random effects. The summary diamond represents the overall meta-analytical estimate with 95% CI. The red bar represents the range of the prediction interval. Tolerance intervals were calculated using the Hoffman and Kringle (HK) method within a one-way random-effects model (Montes et al., 2019). CI = confidence interval; HR = hazard ratio. See the online article for the color version of this figure.

In assessing model fit in terms of parsimony with respect to mortality risk, we also compared a series of multivariate meta-analytic models comparing various personality trait structures/groupings as moderators. Specifically, we assessed the full Five-Factor Model in addition to models reflecting theoretically informed combinations. To evaluate the trait structure that was most parsimonious in accounting for the association between personality and mortality, we assessed each model fit with the Akaike's information

Table 5

Multivariate Meta-Analysis Estimates

Personality trait	Estimate (β)	*z*	*p*	95% CI	HR [95% CI]
Neuroticism	.016	3.235	.001	[.006, .026]	1.02 [1.01, 1.03]
Extraversion	−.026	−2.878	.004	[−.043, −.008]	.98 [.96, .99]
Openness	−.012	−1.477	.137	[−.029, .004]	.988 [.97, 1.00]
Agreeableness	.006	.955	.339	[−.006, .019]	1.006 [.99, 1.02]
Conscientiousness	−.057	−6.313	<.001	[−.074, −.039]	.95 [.93, .96]

Note. CI = confidence interval; HR = hazard ratio.

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Table 6
Meta-Analytic Correlations Among Personality Traits as Reported by Buecker et al. (2020)

Personality trait	*r*	95% CI
Extraversion–agreeableness	.173	[.134, .211]
Extraversion–conscientiousness	.156	[.122, .189]
Extraversion–neuroticism	−.204	[−.256, −.153]
Extraversion–openness	.223	[.177, .270]
Agreeableness–conscientiousness	.221	[.190, .252]
Agreeableness–neuroticism	−.216	[−.265, −.166]
Agreeableness–openness	.167	[.129, .205]
Conscientiousness–neuroticism	−.206	[−.257, −.156]
Conscientiousness–openness	.106	[.069, .143]
Neuroticism–openness	−.076	[−.114, −.038]

Note. CI = confidence interval. From "Loneliness and the Big Five Personality Traits: A Meta-Analysis," by S. Buecker, M. Maes, J. J. A. Denissen, and M. Luhmann, 2020, *European Journal of Personality*, *34*(1), p. (https://doi.org/10.1002/per.222). Copyright 2020 by Sage Publications. Reprinted with permission.

criterion and the Bayesian information criterion. The Akaike's information criterion and Bayesian information criterion reflect the model fit complexity trade-off and therefore can be used to determine the most parsimonious model between competing models, that is, a model that provides the best fit with as few predictors as possible. The model with the lowest Akaike's information criterion/Bayesian information criterion was interpreted as the model that offered the best fit and explanatory power (Vrieze, 2012). The full model incorporating each of the five personality traits possessed the greatest explanatory power (Table 7).

Discussion

This review synthesized an expansive longitudinal research literature on personality trait associations with mortality risk. We found that neuroticism was predictive of premature mortality, whereas conscientiousness and extraversion demonstrated protective effects. Initial significant effects for openness did not withstand sensitivity checks. For neuroticism, the pooled effect sizes were smaller across studies with adjustment for health behavior, a biological marker, or comorbidity, albeit remaining a significant predictor. For conscientiousness, controlling for any biological marker, for example, BMI and systolic blood pressure, was a significant moderator and attenuated the pooled effect of conscientiousness to nonsignificance. As such, the associations for neuroticism and conscientiousness were partly accounted for by health-related factors, which is consistent with conceptual models. In multivariate analyses, the significant effects of each of the three traits persisted when all five were included in the model. In other words, the significant effect for each of them was independent of its relation to any of the other traits. When examining parsimony in predicting mortality risk, the model including the five traits was the most parsimonious. This review advances existing reviews in the area as it synthesizes studies using longitudinal data to evaluate the predictive effect of personality traits on mortality risk. Five of 28 studies included in this meta-analysis were included in previous reviews (Christensen et al., 2002; Jonassaint et al., 2007; Nakaya et al., 2005; Taylor et al., 2009; R. S. Wilson et al., 2005). The reason studies included in prior reviews (Ferguson & Bibby, 2012; Kern & Friedman, 2008; Roberts et al., 2007) were excluded in this meta-analysis was (a) predominantly as a result of a longer follow-up period being available in more recent studies or (b) because the research design (e.g., correlational) or personality measure used in some of the studies did not meet preregistered inclusion criteria. Overall, estimates appeared small; however, a small effect size should be considered important, especially when the outcome, mortality risk, is not easily influenced (Prentice & Miller, 1992) and where the predictive validity of personality traits may have important implications for public health outcomes (Chapman et al., 2010; Cuijpers et al., 2010). Previous more minimally adjusted models of personality traits and mortality risk have demonstrated effect sizes similar in magnitude to commonly considered mortality risk factors (e.g., socioeconomic status, intelligence; Roberts et al., 2007). It is important to remember the estimates under examination in the present review follow adjustment

Table 7
Multivariate Meta-Analysis Moderation of Trait Groupings

Trait grouping	Estimate (β)	*z*	*p*	95% CI	AIC	BIC
All five traits (NEOAC)					−483.26	−462.05
Interpersonal effectiveness (EO)	−.010	−1.428	.139	[−.017, .002]	−455.96	−443.76
NCA	−.008	−1.428	.153	[−.024, .004]		
α or stability (ACN)	−.075	−4.805	<.001	[−.106, −.045]	−225.17	−212.97
β or plasticity (EO)	−.009	−.762	.446	[−.106, −.045]		
β or plasticity (EO)	−.053	−3.216	.001	[−.086, −.021]	−216.57	−204.37
α or stability (ACN)	−.021	−1.807	.071	[−.044, .002]		
Type D (NE)	.000	.017	.986	[−.025, .0255]	−225.87	−213.68
ACO	−.065	−4.944	<.001	[−.091, −.039]		
NC	−.025	−1.889	.058	[−.051, .001]	−214.51	−202.31
EOA	−.039	−2.816	.005	[−.066, −.012]		
NCE	−.035	−3.091	.002	[−.058, −.013]	−214.32	−202.12
OA	−.024	−1.334	.182	[−.058, .011]		
NCEO	−.036	−3.482	.001	[−.057, −.016]	−215.10	−202.90
A	−.007	−.295	.767	[−.056, .041]		

Note. CI = confidence interval; AIC = Akaike's information criterion; BIC = Bayesian information criterion; N = neuroticism; E = extraversion; O = openness; A = agreeableness; C = conscientiousness.

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for a large number of covariates, many of which are underlying health-related mechanisms. While some of the prediction intervals might contribute to lack of confidence in future studies, it is important to remember that broad prediction levels are common and, therefore, should not be given undue significance (IntHout et al., 2016).

Neuroticism emerged as a robust predictor of mortality risk, with future studies likely to find similar patterns (e.g., prediction interval). There was a reduction in the association when health-related factors were accounted for. This is as expected due to neuroticism likely exerting its influence on mortality risk through a broad range of mechanisms (for review, see Grogan et al., 2024). These mechanisms include various behaviors (e.g., smoking; Graham et al., 2017) and biological systems (e.g., cardiovascular; Jokela et al., 2014), which have been tested directly in the context of their indirect link. In broader literature, neuroticism has been widely associated with a vast range of health processes and outcomes, for example, accelerated aging processes related to telomere attrition (van Ockenburg et al., 2014) and mitochondrial health linked to diabetes and depression (Oppong et al., 2022), cognitive decline (Luchetti et al., 2016), and increased dementia risk (Aschwanden et al., 2021), and low neuroticism has been associated with higher interleukin-6, a marker of systemic inflammation (Graham et al., 2018).

Age significantly moderated the effects of neuroticism on mortality risk, accounting for a substantial proportion of the variance between studies. The association of neuroticism with mortality was stronger in younger samples, suggesting that neuroticism is particularly relevant for premature mortality (deaths occurring at younger ages). There has been inconsistent evidence that the associations between personality and mortality risk differ between males and females (Friedman et al., 2010; Korten et al., 1999; Ploubidis & Grundy, 2009; Taylor et al., 2009). While differences between males and females should be considered in personality research (e.g., Hampson & Friedman, 2008), we did not find that sex was a moderator of between-study differences. Literature suggests that high neuroticism is a major risk factor for depressive symptoms (American Psychiatric Association, 2022; Hakulinen et al., 2015; Kotov et al., 2010). While just a few studies could be compared, we observed no significant difference based on whether studies adjusted for depression or depressive symptoms.

Extraversion was associated with a decreased mortality risk. Geographical location did account for a substantial proportion of variance between studies. Like Graham et al. (2017), who observed differences between U.S. samples versus non-U.S. samples, this study observed that in North America and Australia, extraversion was associated with decreased mortality compared with studies from the United Kingdom, Europe, and Japan. The differences between regions may also be because of confounding with the measures used. Decreased mortality risk was observed only among studies using scales based on the Five-Factor family, compared with Eysenck Inventories. Previous research has suggested weaker effects associated with Eysenck Inventories compared to other measures (e.g., Neuroticism, Extraversion, and Openness inventories; Kotov et al., 2010; Malouff et al., 2005). Also, the percentage of deceased participants accounted for a significant amount of variance between studies. For every one-unit increase in the percentage of deceased participants, the mortality risk increased. This would suggest that statistical power is an important consideration when examining extraversion. Other possibilities for the differences across nations may be because of person-culture fit, health-behavior links, or socioeconomic returns. For instance, it may be that the trait is more culturally prized and leads to more social integration in highly individualistic societies, whereas in other cultures that are more collectivistic or egalitarian, the health benefit of extraversion may be much weaker. On health behavior, it may reflect differences in physical activity levels, where greater effects of extraversion on physical activity have been observed in North America, compared to the European Union and Japan (K. E. Wilson & Dishman, 2015). On socioeconomic returns of extraversion, it may translate to higher income and greater occupational status in employment markets with large health care costs (e.g., United States), whereas flatter wage structures and universal health coverage in other nations (e.g., European Union) may equate to less direct impact on mortality risk (e.g., McCann, 2025).

Conscientiousness is most frequently reported as associated with mortality risk and, indeed perhaps, health outcomes more broadly. As such, the prediction interval may be surprising in that it was quite broad and crossed the threshold for significance. However, it is important to reemphasize that broad prediction intervals can be quite common, particularly when heterogeneity is high. It is also informative that controlling for any biological marker of health, for example, BMI and systolic blood pressure, was a significant moderator of pooled effect leading to nonsignificance in the conscientiousness–mortality risk relation. Coupled with the previously wide variety of health-related associations, it would be very important for future work to reflect on the types of variables included in adjustments. Simply put, many of these are likely moderators and/or mediators linking the trait to risk of mortality and may lead to incorrect conclusions. These findings suggest that physiological factors may be particularly important to consider in the context of conscientiousness. Of course, that does not preclude other related factors given these systems involve complex interplay across multiple biopsychosocial systems. There was evidence of publication bias as indicated by the trim and fill method and PET–PEESE approaches. While the trim and fill method would suggest that there is not a significant effect following adjustment for bias, it is important to note that, as previously alluded to, this method is very sensitive to estimates that demonstrate high heterogeneity, as we see with conscientiousness. Conversely, the PET–PEESE approach in assessing publication bias adjusts for bias and, in doing so, demonstrated that a significant effect persisted.

Openness was initially associated with a decreased mortality risk. There were significant differences between studies. The type of scoring was a significant moderator, with studies using categories reporting a protective pooled effect, compared with studies using continuous scoring, which did not. However, there were only three studies using categorical scoring included in the analysis. Removing these categorical studies from the meta-analysis did not change the direction of effects but attenuated them to nonsignificance. Once adjustments were made for small-study bias, there was no clear evidence of a true effect. This was further echoed when examining openness within the multivariate analyses, where a significant univariate effect did not withstand the inclusion of the remaining traits. This would suggest that openness is not directly predictive of mortality risk. Of course, that is not to suggest it is not related to health processes; it just appears, at least in this review, that it is not directly related to mortality risk. Agreeableness was not associated with mortality risk. Between-study heterogeneity was very high. Results of this meta-analysis were in line with our preregistered expectations that

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agreeableness was not associated with mortality risk and in contrast with some other research that did find meta-analytic protective effects for agreeableness (e.g., Graham et al., 2017). Despite this, it is important to discuss findings to prevent outcome reporting bias and the potential for Type II error (Kirkham et al., 2018; Litière et al., 2007). Differences between studies may provide insights into variability in results. Shorter follow-up periods and smaller numbers of deceased participants were significant moderators of differences between studies and could explain why effects were not detected for agreeableness, highlighting the importance of consideration of these study-level factors in personality–mortality research.

The broad personality factors contain several facets that themselves reflect diverse responses (Chapman et al., 2020). However, this review synthesized research on broad factors and did not explore individual facets. Research in the area of facets as predictors of mortality risk may be important to explore (Butler et al., 2023; Chapman et al., 2020; Terracciano et al., 2008). For example, the facet of impulsivity has been shown to be an independent predictor of mortality risk in individuals with alcohol use disorders (Blonigen et al., 2011). Additionally, openness facets of feelings and actions, related to greater emotional awareness and curiosity, have been associated with longevity in patients with coronary artery disease (Jonassaint et al., 2007). Furthermore, a large longitudinal study of middle-aged and older adults reported that the industriousness facet of conscientiousness was a predictor of longevity (Stephan et al., 2019). Literature also suggests that even more refined personality items may be informative in the context of mortality risk (e.g., Stephan et al., 2025). Additionally, personality traits appear to change across the life course, which would be an important consideration for future work, particularly as they pertain to important life outcomes (Wright & Jackson, 2023, 2025). However, a coordinated meta-analytic study suggests that personality trait changes have little impact on mortality risk (Willroth et al., 2025). Heterogeneity was not accounted for by the number of covariates a study included. However, the type of covariate did make a difference in some cases. Studies that adjusted for health-related factors showed an attenuated effect, potentially suggesting that health could be part of the causal chain connecting personality to mortality (Graham et al., 2017; O'Súilleabháin et al., 2021; Turiano et al., 2015). It is clear from these findings that the selection of possible variables in future analyses requires thoughtful consideration (Beck & Jackson, 2022; Grogan et al., 2024).

Strengths and Limitations

This was a rigorous and comprehensive review of longitudinal research, comprising 569,859 participants and 43,851 deaths and spanning four continents. It was carried out in adherence with open science principles as a core feature, using an unbiased and thorough search and rigorous review methods (Johnson, 2021; Segerstrom et al., 2023). Data were combined from coordinated meta-analytic studies of several cohort panel studies totaling 2,025,882 person-years and included nearly twice that from other additional studies with 3,952,113 person-years. The use of a random-effects model was justified by considerable between-study heterogeneity. Examining multivariate effects is also a considerable strength of this review, as is the methodological rigor and multiple reporting systems used throughout.

Limitations must also be noted. Findings stemmed from high-income countries with predominantly White population samples and fewer cultural and societal barriers to data collection. Future studies need to focus on lower to middle-income countries, particularly those in far-ranging and geographically isolated communities. This limitation is further compounded by all included studies being in the English language. We attempted to counteract this through consultation with a translation specialist and reviewing several artificial intelligence translation tools to assess the possibility of incorporating several languages into our inclusion criteria. We concluded that the quality, and in particular, the accuracy of the artificial intelligence translation languages, was not sufficient to warrant inclusion and would likely undermine the rigor of the review. No doubt, future developments will lead to advances within this space. We also took one approach to the conceptualization of personality. There are numerous perspectives, and these should be considered in future work. There is also a need for greater numbers of studies to ensure adequate power when examining moderation. Additionally, while the inclusion criteria were carefully defined to increase reliability of findings, having more relaxed inclusion criteria in the future may allow greater statistical power and may provide more information. However, a recent article emphasized that while including more studies in a meta-analysis may increase statistical power, this could compromise quality through increased heterogeneity and risk of bias (Buecker et al., 2023). Finally, the examination of competing trait groupings within the multivariate analysis was exploratory and somewhat crude. That is, irrespective of the conceptual similarities, there are numerous approaches to the measurement of those various constructs, and that should be considered when interpreting these findings.

Conclusion

This review identified significant pooled effects across all included studies for neuroticism, extraversion, and conscientiousness, but not agreeableness. Initial significant effects for openness did not withstand various checks. We found evidence that higher neuroticism was associated with increased mortality risk, with stronger effects experienced in younger populations. Extraversion was associated with a decreased risk of mortality, notably in North America and Australia. Conscientiousness was also related to a decreased mortality risk. Effects for neuroticism and conscientiousness were attenuated when adjusting for health-related factors, to nonsignificance in the case of conscientiousness. Further work is needed in multiple respects, including a closer examination of openness and agreeableness, as sample size and follow-up periods may be important to consider. We found that each significant effect for neuroticism, extraversion, and conscientiousness persisted when adjusting for the effects of all the traits. When examining the model fit on mortality risk, the model incorporating the five personality traits was the most parsimonious. Taken together, this systematic review and meta-analysis brings together extensive longitudinal literature, concluding that personality traits are vital determinants of longevity.

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