Acta Psychologica 233 (2023) 103833

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Worker aging, control, and well-being: A specification curve analysis

Rachel S. Rauvola [a,*], Cort W. Rudolph [b]

[a] Department of Psychology, DePaul University, Chicago, IL, USA
[b] Department of Psychology, Saint Louis University, Saint Louis, MO, USA

ARTICLE INFO

Keywords:
Aging
Lifespan development
Control
Well-being
Specification curve

ABSTRACT

Among the many work (and life) characteristics of relevance to adult development and aging, various forms of control are some of the most extensively and diversely studied. Indeed, "control," whether objectively held (i.e., "actual" control), perceived, or enacted through self-regulation, is a concept central to our understanding of person-environment interactions, development, and well-being within and across life domains. However, variability in conceptualization and analysis in the literature on control presents challenges to integration. To partially address these gaps, the present study sought to explore the effects of conceptual and analytical specification decisions (e.g., construct types, time, covariates) on observed control-well-being relationships in a large, age-diverse, longitudinal sample (Midlife in the United States I, II, and III datasets), providing a specification curve analysis (SCA) tutorial and guidance in the process. Results suggest that construct types and operationalizations, particularly predictor variables, have bearing on observed results, with certain types of control serving as better predictors of various forms of well-being than others. These findings and identified gaps are summarized to provide direction for theoretical clarification and reconciliation in the control and lifespan development literatures, construct selection and operationalization in future aging and work research, and inclusive, well-specified interventions to improve employee well-being.

1. Introduction

Control is among the most integral components of psychological theory, standing the test of time as central to our understanding of development and well-being within and across life domains. Indeed, apart from its philosophical significance, control has been leveraged in theoretical and empirical work pertaining to lifespan development and (occupational) health, among other areas (e.g., Demerouti et al., 2001; Schulz & Heckhausen, 1999). It is critical to modern conceptions of life outcomes (e.g., health and well-being, social status; Chipperfield et al., 2017; Lachman & Weaver, 1998b; Thompson & Spacapan, 1991) and self-regulatory processes that contribute to development and life success (e.g., primary and secondary control striving; Heckhausen et al., 2010, 2019), as well as processes and outcomes specific to the work context (e.g., control striving at work, work satisfaction and well-being; see review in Rauvola & Rudolph, 2021). The contention that control "matters" for workers across the lifespan is thus well established in a broad sense; beyond this, however, the abundance of control constructs, theories, and mixed findings in the literature make integration and practical translation challenging.

Indeed, across theory and research, "control" can be construed and assessed in different ways, each with important (and distinct) implications for empirical predictions and findings. As with many other core psychological concepts, researchers have a great deal of discretion and choice in how they measure (i.e., operationalizing forms of control) and model control (i.e., which combination of predictors, outcomes, and covariates are included in analyses and in what ways). Unfortunately, given the sheer volume of possible model choices to make, decisions are often relatively arbitrary, reflective of researchers' particular interpretations of theory and motivated interests, and selectively reported (Simonsohn et al., 2020). These "researcher degrees of freedom" (Simmons et al., 2011, p. 1360) stand to majorly impact observed findings and subsequent conclusions: with such empirical and analytical variety come challenges in comparing and integrating findings in the control literature. Although no one study nor approach can resolve this issue, there are methods to foster transparency around and discussion of influential specification decision-making, which will increase the chances observed differences are not due to arbitrary decisions and reporting and ultimately improve our science and practice. Ambiguity around how and which analytical decisions were made obfuscates the

* Corresponding author at: DePaul University, Byrne Hall 407, Chicago, IL 60614, USA.
E-mail address: rrauvola@depaul.edu (R.S. Rauvola).

https://doi.org/10.1016/j.actpsy.2023.103833
Received 7 July 2022; Received in revised form 14 December 2022; Accepted 5 January 2023
Available online 7 January 2023

source of result divergence or even convergence, with readers left to wonder whether divergent results are attributable to differing (valid) theoretical and statistical orientations (i.e., different standards for deeming specifications to be reasonable) or to selective presentation (i.e., arbitrary reporting based on the same specification standards; see parallel topical discussions in Frey et al., 2021; Masur, 2021; Simonsohn et al., 2020).

The present study sought to highlight these issues in relation to aging and the work context, providing an illustrative empirical demonstration of, tools for, and guidance on generating and evaluating analytical specifications with a large, variable-rich, longitudinal dataset. By systematically considering a range of control construct types, operationalizations, and model specifications in relation to various well-being outcomes in our analyses, we generate both informative conclusions for the literature (i.e., findings regarding the nature, presence, and relative magnitude of relationships between forms of control and well-being among employed adults across two decades) and a guide and example for (aging) researchers seeking to address similar concerns about the basis and effects of specification decision-making in their area of the field. For this latter portion of our work, we apply a relatively novel and flexible analytical method (i.e., specification curve analysis), which has both strengths and limitations especially relative to other analytical approaches and for different purposes (e.g., exploratory vs. causal effect estimation); we discuss these further throughout the manuscript to provide a critical perspective on and recommendations for the systematic consideration of model specifications in the aging literature.

In the following sections, we outline and define control constructs, provide a review of relevant workplace and lifespan literature, and discuss different approaches to assessing analytical specification robustness. In the process, we establish the foundation for our research questions, study design, and analytic approach (see also Table 5, which maps study goals, analyses and specifications, findings, and conclusions).

1.1. Control constructs

At the broadest level, we define control at the person level as the discretion, power, or influence an individual has over their actions in a given situation, in combination with the ability to engage in actions and/or receive desired outcomes as a result of these actions (Rauvola & Rudolph, 2021). Specific forms of control fall within this general definition and can be thought to correspond to one of three possible categories: "actual," perceived, and enacted control. We discuss both domain-general (i.e., control across life spheres) and domain-specific control forms, focusing our latter discussion on work-related control in light of its centrality to and influence on health and well-being, identity, social status, relationships, and various aspects of adult development across the lifespan (e.g., Beatty & McGonagle, 2018; Blair, 2000; Kanfer et al., 2013; Lubben & Gironda, 2003). Indeed, many individuals spend much of their adult lives in the workforce generating social connections, acquiring knowledge, skills, and coping strategies, setting and reaching goals with implications for broader motivational systems and capacities, gaining meaning and purpose, and garnering a professional sense of self and social position (in and outside of the organization) over the course of their careers. This life domain is particularly appropriate to study given its potential for interventions as well: organizations are interestingly positioned with a great deal of discretion over how much control and autonomy their employees have, perceive, and can enact, and they wield this power during much of adults' lives through various means (e.g., during the workday, after work through spillover into home life, sleep; e.g., Knudsen et al., 2007) and with implications for individuals' control in other domains (e.g., the "actual" control they have in society as a function of income and occupational prestige).

More specifically, *"actual" control* concerns an individual's objective level of available choices, among different goal striving means or actions, in a given context or situation. This degree of choice is contingent not only upon the mere availability of alternative action(s), but also upon an individual's ability to perform chosen actions and/or their ability to obtain certain outcomes as a result of their choice and actions. Thus, individuals possess "actual" control when they can choose how to act and are at least somewhat effective in either engaging in this action or bringing about a desired outcome. For example, when tasked with leading a new project at work, an individual possessing "actual" control would have both a degree of choice in how to plan and structure the project (e.g., timeline, team members, processes), and would have personal and contextual resources available to execute the project and/or receive commensurate feedback and rewards upon successful execution. Unfortunately, "actual" control often cannot be measured directly (save for in rigorously controlled experimental manipulations), and instead must be inferred through personal (e.g., sociodemographics that impact goal-relevant means and ends) and contextual attributes (e.g., job demands and resources that provide control opportunities and means/ends). Still, findings in the literature have linked "actual" control attributes such as gender, socioeconomic status, and occupational control characteristics to differences in perceived control as well as well-being (e.g., Bobak et al., 1998; Lachman & Weaver, 1998a; Thompson & Prottas, 2006). "Actual" control is also a core component of lifespan development theory, construed as a resource or constraint that shapes goal selection and striving with age (e.g., social class' influence on stress and health, dynamic interactions between workers and their workplace's opportunities and limitations; Wahl & Gerstorf, 2018) or more directly, in the form of age-related gains and losses (e.g., Schulz & Heckhausen, 1996, see also discussion in Hamm et al., 2021).

In contrast, *perceived control* refers to individuals' beliefs about their available choices, and their ability to perform chosen actions and/or obtain certain outcomes as a result. To take the earlier example, when tasked with leading a new project at work, an individual who perceives control believes that they have a choice in how to plan and structure their project, and that they will be able to execute the project and/or receive desired outcomes following from their execution. A variety of perceived control constructs fall within this purview, including but not limited to expectancy, self-efficacy, (job) autonomy and control, instrumentality, and locus of control. Such forms of perceived control have been similarly linked to well-being within particular contexts (e.g., at work; Liu et al., 2018; Ng et al., 2006; Siu et al., 2005; Spector, 1986) and in life more generally (e.g., Gerstorf et al., 2010; Infurna et al., 2011; Liu et al., 2018). As with "actual" control, perceived control is similarly treated as a resource (or constraint, when low) with influence over developmental self-regulation in lifespan theories, and it is formally included in many models of aging and health (see reviews in Lachman et al., 2011; Robinson & Lachman, 2017). There is debate about the degree to which "actual" control must be perceived in order for it to be influential (e.g., Langer, 1979), with many authors contending objective levels of control are of relatively little import when compared to individual beliefs (e.g., Lachman et al., 2015).

Rather than eschew one or the other form of control, however, it may be that the relative contributions of "actual" and perceived control to outcomes are more apparent when studied alongside enacted control, and they can demonstrate more complex and interactive dynamics when considered within the broader lifespan context. *Enacted control* refers to individuals' engagement in a variety of strategies to self-regulate their development and functioning. Generally speaking, enacted control consists of two classes of strategies: primary and secondary control striving. Whereas primary control striving entails attempts to change one's environment to be in line with needs and goals, secondary control striving entails attempts to change oneself (i.e., needs, goals) to be in line with opportunities and constraints in the environment (Heckhausen et al., 2010; see also the parallel tenacious goal pursuit and flexible goal adjustment literature from Brandstädter & Renner, 1990). Thus, unlike "actual" and perceived control, which remain objective or perceptual, enacted control consists of a range of (pro)active adjustments and methods engaged by individuals to support well-being. This situates control enactment within lifespan development theories as motivational, self-regulatory mechanisms: rather than serving as resources or constraints, primary and secondary control encompass the very goal selection and striving processes individuals engage in based upon their personal and environmental circumstances.

As with "actual" and perceived control, enacted control has also been linked to well-being outcomes such as positive and negative affect, satisfaction, and mental health within certain contexts (e.g., work; Abraham & Hansson, 1996; Körner et al., 2012) and in life more generally (e.g., Haase et al., 2012; Heyl et al., 2007). However, it is apparent that these relationships, and the adaptivity of different forms of enacted control, are at least partly dependent upon personal factors that affect "actual" and perceived control (e.g., age-related changes, Broadbent et al., 2014; functional (in)dependence, Hamm et al., 2017; daily workload, Hoppmann & Klumb, 2012; employment status, Körner et al., 2012). Indeed, across the lifespan, individuals experience increases, decreases, and stability in "actual" control (i.e., functioning in various areas, available resources and capacities), and their levels of perceived control vary as well, serving protective and adaptive functions by offsetting age-related losses and capitalizing on strengths and gains (e.g., through focus on different life domains, levels, perspectives; through goal adjustment and realistic expectation setting; Infurna et al., 2013; Lang & Heckhausen, 2001). Thus, primary and secondary control striving are not inherently "good" in and of themselves. Instead, they promote well-being within an individual's personal and environmental context.

1.2. Specifying control and its outcomes in aging research

Clearly, there is a good deal of theory and literature supporting the idea that control opportunities (i.e., "actual" control, perceived control) and striving (i.e., enacted control) are related to well-being across the lifespan. An abundance of literature has been dedicated to considering one or more forms and domains of control in relation to important outcomes (e.g., well-being) with age (see qualitative and quantitative reviews in Agrigoroaei & Lachman, 2010; Heckhausen et al., 2021; Lachman & Burack, 1993; Lachman et al., 2011; Ng & Feldman, 2015; Rauvola & Rudolph, 2021; Robinson & Lachman, 2017; Rodin, 1986; Skinner, 1996; Spector, 1986). We focus here on a sample of studies all hailing from largely the same theoretical space but with diverse control and well-being outcome operationalizations; we do so to highlight the range of reasonable specifications that control and aging scholars have to "choose" from in designing their studies and analyzing their data, and call attention to the broader population of possible, reasonable specifications which often go unreported.

Shane and Heckhausen (2012), for example, conducted a work domain study of perceived and enacted primary control congruence, finding that individuals with congruent primary control enactment and perceived control at work at Time 1 reported positive effects of their job on mental and physical well-being at Time 2 (eight to ten years later; see also Shane & Heckhausen, 2016). Grümer et al. (2013) similarly investigated interplay between perceived and enacted control in particular domains (i.e., work, family) in light of social pressures relevant to work and family (e.g., fewer available jobs/training, unreliability of friends/contacts) and individuals' perceived control over these demands. In a cross-sectional study, the authors found support for the idea that perceived control-congruent enacted control strategies were most adaptive with respect to subjective well-being, such that goal engagement was positively linked to subjective well-being when perceived control was high and goal disengagement was positively linked to well-being when perceived control was low. Recent multilevel work has considered control beliefs at general (i.e., beliefs about perceived constraints in life) and day levels (i.e., beliefs about control over daily events) in relation to well-being (e.g., Koffer et al., 2019), control diversity and stressor reactivity (i.e., a summary metric of cross-domain control beliefs; Drewelies et al., 2019), actor and partner state and trait control beliefs (Drewelies et al., 2020, and forms of perceived and enacted control (specifically relative to personal goals and adjustment), accounting for "actual" control-relevant sociodemographics (e.g., age, gender, socioeconomic status; Hamm et al., 2022).

In just this selection of studies alone, it is apparent how a great deal of variability in construct operationalizations (e.g., forms and sub-types of control considered, domain specificity vs. generality of control, construct coverage) and analytic choices (e.g., treatment of variables as predictors vs. covariates, disentangling between- vs. within-person effects) can manifest within a shared theoretical vein. Especially as the study of aging moves necessarily toward more integrative and transparent science (Hill & Stine-Morrow, 2022; Hofer & Piccinin, 2010; Isaacowitz & Lind, 2019), it is increasingly important to incorporate supplemental considerations, alternative testing, and robustness checks into our studies. The area of aging and control is a prime place to initiate some of these efforts, as it sits at the confluence of an abundance of constructs and a generally cohesive set of theoretical tenets regarding the adaptive roles of control in adult development and coping. Many major questions remain in our knowledge of the importance of different forms of control, at what levels and in what domains these forms of control are best and most usefully assessed, and how forms of control interact over time (e.g., Lachman et al., 2015; Robinson & Lachman, 2017). In light of work's central role in adult development, and the various forms of control that emerge thence, situating this investigation in reference to domain-general and work-specific control constructs allows us to consider these questions in multiple important senses.

To answer these questions, there appear to be three major, interrelated areas in the literature that require further attention. These areas are 1) simultaneous consideration of a range of domain-general and -specific forms of control in predicting well-being, 2) investigation of control and well-being phenomena, within and between subjects, over time, and 3) evaluation of model specification decisions' bearing on observed results (see Table 5). We discuss approaches to evaluating model specifications in detail next, employing newer methods and custom tools for specification evaluation in our study to both a) generate informative findings for the literature about modeling control and well-being phenomena and b) provide a structured example of and guidance on how future aging research can identify and evaluate viable model specifications.

1.3. Model specifications

When looking across and synthesizing any literature, we must wonder: are we encountering conclusions based upon different but equally valid specification standards, or are we surveying a sample of conclusions that only comprise an (arbitrary) portion of the same universe of reasonable specifications? Different methods have been historically used to assess or report how robust a set of findings are to alternative model specifications, such as extreme bounds analysis (i.e., testing regressions for all covariate combinations, originating in the field of econometrics, Leamer, 1983) or advocating for reporting the variance of point estimates across a selection of alternative specifications (e.g., standard deviations; Athey & Imbens, 2015). Specification curve analysis (SCA) is a newer approach to this issue and offers a number of distinct advantages over (as well as some notable limitations and concerns relative to) other approaches; we use this method for our illustrative empirical demonstration and provide guidance and other analytical tools to aid researchers in exploring the benefits and limitations of this method (and the questions it ought and ought not be applied to answer) in their work.

SCA refers to a statistical technique that runs all or a selection of reasonable model specifications (i.e., in terms of theoretical relevance, statistical validity, and non-redundancy with other specifications; Simonsohn et al., 2020), organizes resulting effect sizes by magnitude in a visual plot, and allows for various distributional and decomposition-based assessments (e.g., variance explained by model components).

This approach allows a multitude of potential predictor and outcome variable operationalizations, covariates, model configurations, transformations, and data inclusion/exclusion criteria to be simultaneously estimated. Then, the results can be used to interpret the consequences of analytic choices in study models, with the tested specifications serving as a representative (rather than a selective) sample of possible analyses conducted with a given dataset and research question. Unlike other methods for assessing alternative specifications, SCA provides clear structure and parameters for generating the population of specifications to consider, and it produces accessible, organized, and variously informative results that speak to sources of variability and finding robustness across all operationalization decisions deemed valid and reasonable (Simonsohn et al., 2020). We walk readers through the core steps in specification set generation and subsequent results interpretation, and we accompany this working example with an interactive mixed-effects modeling website (see https://cortrudolph.shinyapps.io/CONTROL_APP/ discussed in more detail later) for use in exploring questions and model combinations that are not well implemented within available SCA tools.

Original hypotheses, methods, and analyses for the present study were preregistered (https://osf.io/2qjcr/) and amended here: (https://osf.io/nd943/). Whereas it was originally hypothesized that various forms of control would be positively related to one another cross-sectionally and over time, in addition to manifesting variability at both the within- and between-person levels, the present study instead aimed to answer the following research questions:

Research Question 1. How do conceptual specification decisions, such as the consideration of different types and operationalizations of control and well-being, affect observed control-well-being relationships?

Research Question 2. How do longitudinal data analysis specification decisions, namely accounting for time and data non-independence, affect observed control-well-being relationships?

Research Question 3. How do other reasonable, conceptual and analytical model specification decisions (e.g., data exclusion criteria, covariates, interactions) affect observed results?

Our findings on conceptual and analytical decisions' bearing on observed control–well-being relationships over time are of direct interest (i.e., adding to the literature simultaneously considering multiple forms of control and well-being in the context of aging and work over time) and provide a worked example of interpreting SCA results for the aging literature more broadly.

2. Methods

2.1. Sampling & participants

The present study used data from three waves of the longitudinal Midlife in the United States (MIDUS) dataset. For data to be considered for inclusion in the present study, participants were matched across all three waves (using the unique identifiers provided to them in the MIDUS datasets) and those who had complete data for variables of interest were used in analyses (i.e., at the composite variable level rather than at the item level). Based on these criteria, the final sample for this study was $N = 769$ ($N = 769 \times 3$ waves $= N_{obs} = 2307$) and had a mean age of 40.14 (S.D. = 8.20) at Time 1. The sample was relatively balanced with respect to reported gender (53.71 % male, 46.29 % female) and reported working an average of 42.58 h per week (S.D. = 12.81) at Time 1. The sample was primarily white (95.97 %) and had some representation of other racial/ethnic backgrounds (1.95 % Black and/or African American, seven "Other", three Asian or Pacific Islander, two Native American or Aleutian Islander/Eskimo, two multiracial, two declined to respond). Finally, participants were relatively well educated, with the majority reporting having completed at least some post-secondary education (15.21 % one to two years of college with no degree, 5.98 % three or more years of college with no degree, 7.28 % two-year college/vocational/associate's degree, 29.52 % four-year college/bachelor's degree, 4.16 % some graduate school, 12.22 % master's degree, 5.85 % doctoral/professional degree) and much fewer with high school or less education (two individuals completed eighth grade/junior high school, twelve individuals completed some high school, four individuals received GED, 17.43 % graduated from high school). The full MIDUS sample from Waves I-III ($n = 7108$ at Wave I, $n = 4963$ at Wave II, $n = 3294$ at Wave III) was also used in certain analyses considering whether findings differed depending on different inclusion criteria (i.e., as specified in Research Question 3). Full demographic details of this sample are available in MIDUS documentation (e.g., Brim et al., 2019) and are summarized in our online appendix, and variable-level observation counts are reported in our results.

2.2. Materials

Several variables of interest were included in the present study from the MIDUS I, II, and III datasets (see Table 1). Any discrepancies in measurement (e.g., added items, additional sub-scales) were avoided in the present study to facilitate consistency across the three waves. Only two composite measurements (chronic conditions and socioeconomic status, described below) outside of those already available in the dataset were computed; otherwise, established composites available in the MIDUS datasets were used for analyses. Recoding with Occupational

Table 1
Study variable categories, domains, constructs, and operationalizations.

Variable category	Domain	Construct	Operationalization
Actual control	General	Age	Self-reported age in years
		Gender	Self-reported sex (female, male)
		Socioeconomic status	Composite calculated from education level, financial situation, difficulty paying bills, annual wage from previous calendar year, money available for basic needs (as in Gruenewald et al., 2012; Zilioli et al., 2017)
	Work	Objective job control	O*NET (2019) occupation data (linked via Census occupation codes) on freedom to make decisions, decision making frequency, decision impact on co-workers or company results, structured vs. unstructured work
Perceived control	General	Sense of control	Personal mastery, perceived constraints (Prenda & Lachman, 2001)
	Work	Perceived job control	Frequency of job decision authority experiences (items based on Karasek et al., 1981; Karasek & Theorell, 1990)
Enacted control	General	Primary control	Persistence in goal striving (Wrosch et al., 2000)
		Secondary control	Positive reappraisals, lowering aspirations (Wrosch et al., 2000)
Well-being	General	Depression	Screening version of the World Health Organization's Composite International Diagnostic Interview (Kessler et al., 1998; World Health Organization (WHO), 1990) assessing depressed affect and anhedonia
		Physical health	Self-rated physical health, chronic condition incidence (as in McGonagle et al., 2015)
		Life satisfaction	Satisfaction with different life domains (Prenda & Lachman, 2001)
		Psychological well-being	Autonomy, environmental mastery, personal growth, positive relations with others, purpose in life, self-acceptance (Ryff, 1989)

Information Network (O*NET) data was also performed, linking occupational codes to work attributes available in the O*NET Work Context dataset (National Center for O*NET Development, 2019). Full details regarding study variables, reliability levels, and recoding and composite creation procedures are available in our online appendix (OA: https://osf.io/2qjcr/). In service of openness, all data and R syntax to reproduce the analyses presented here are also available in our OA: https://osf.io/nd943/.

2.3. Analyses

Following planned data cleaning and matching, descriptive assessment, and other pre-registered analyses (e.g., measurement invariance assessment; see OA), specification curve analyses were conducted using the {specr} package in R (Masur & Scharkow, 2020). To conduct these, a mixed-effects model function was specified for use in the specification curve analyses, including a random intercept for each participant to account for the nested structure of the MIDUS data and data non-independence. In addition, a range of reasonable model specifications (described next) were identified, defined, and tested to the extent possible within the parameters of the statistical package and while prioritizing research question investigation, interpretability, and computational efficiency. More specifically, all grand mean-centered independent (control) and uncentered dependent (well-being) variable operationalizations, covariates (age, sex, SES, time lag between waves), and data subsets (full sample, sample with complete data at the composite level, sample with incomplete data) were included as arguments in generating the specification curve. We included the latter data subset (i.e., sample with incomplete data) as one form of assessing whether nonresponse or attrition may result in different patterns of results when longitudinal data are assessed prematurely (i.e., before additional waves have been collected) or selectively (i.e., by focusing on only certain waves of a longitudinal collection), while the covariate combinations included represent common control variable sets in the literature (e.g., Barlow et al., 2022; Hamm et al., 2022). Variables were standardized prior to analyses as well to facilitate the interpretability of observed effects (i.e., to return standardized regression coefficients that would be appropriately ranked, given different variable scalings). Specification curve variance components were decomposed and R^2 values computed for different decision classes and model specifications as well. Finally, resources were compiled for investigating areas of our research questions not best answered or testable through specification curve analyses (i.e., the effects of including interactions and/or within- and between-person level centered predictor variables in models).

2.4. Identifying specifications

To determine our set of reasonable specifications, we followed steps outlined by Simonsohn et al. (2020) and used in other published literature (e.g., Del Giudice & Gangestad, 2021; Masur, 2021). First, we identified analytic decisions key to translating our core hypothetical relationship of interest (i.e., the control-well-being relationship) into a statistically testable argument. In considering the literature, we identified four decision sets of note: how “control” is operationalized, how “well-being” is operationalized, what covariates are included in analyses, and methods of handling data missingness (i.e., data subsetting). We also considered the equivalence (i.e., arbitrariness and interchangeability) of our specifications in the process (Del Giudice & Gangestad, 2021); our specifications were deemed to fall within both principled equivalence (i.e., type “E” decisions) and uncertain equivalence (i.e., type “U” decisions) categories, while principled non-equivalence was deemed unlikely (i.e., type “N” decisions, which are often based on practical limitations which would not manifest for scholars working with archival MIDUS data). We considered a simple (assumed) causal structure as most plausible, wherein control influences well-being without implied mediating processes, confounders, or non-causal paths modeled. While we were using SCA for more exploratory and summary ends rather than for causal effect estimation, it is still important to specify this model to set boundaries for the specification space, as well as evaluate decisions' (non)equivalence within these bounds. Equivalence of constructs is of particular import for confirmatory and causal tests, whereas constructs that are not directly exchangeable can be included in more exploratory settings if results are interpreted accordingly (discussed more later). That is to say that, although the operationalizations we included are not directly interchangeable versions of one another (e.g., “chronic conditions” vs. “self-acceptance” are not different measures of the same precise well-being variable), they are relevant to include to the extent that a study is aiming to explore association presence and strength under certain conditions rather than inferentially test causal effects.

After establishing key decision points, goals, and model boundaries, we identified the reasonable, conceivable ways these model decisions could be made. We identified a comprehensive set of operationalizations across waves of the MIDUS data, commonly used covariates in the aging and control literature reviewed earlier, and commonly employed data exclusion criteria to this end. Finally, we generated a comprehensive set of combinations of these decisions, making sure to remove invalid or redundant combinations in the process (Simonsohn et al., 2020). We did not include higher-order terms, additional covariates (e.g., race/ethnicity, marital status), functional time parameters, variable transformations, or model estimators in our specifications due to issues of non-equivalence, interpretability, or statistical package limitations; the focus and scope of our specification approach (e.g., specific decision classes, volume of decisions and alternatives) is similar to others in the psychological literature (e.g., Masur, 2021; Orben & Przybylski, 2019; Steegen et al., 2016) but focused on aspects of decision-making characteristics of the aging, control, and work literature specifically.

2.5. Interpreting results

There are a variety of ways to interpret and present the results of specification curve analyses (e.g., Del Giudice & Gangestad, 2021; Frey et al., 2021; Masur, 2021; Simonsohn et al., 2020), and their appropriateness and applicability depend on the nature of a study's data and methodological approach (i.e., experimental vs. observational), and its inferences of interest. For purposes of the present study's research questions, and given the volume of specifications estimated, we focus on those results most broadly informative for interpreting existing control and aging literature as well as designing future studies: median effect sizes, decomposed variance explained (i.e., R^2 values), and systematic effects patterns observed visually for both general and specific analytical choices. The median effect size provides an index of central tendency that can be compared across specifications, while accompanying effect size ranges and other reported parameters, as well as plots, provide information about the nature and spread of effects across various model specifications. As such, researchers will find this information useful for determining under what circumstances effects change sign, vary in magnitude, or are not observed. Decomposed variance explained informs researchers about the sources of variability in observed effects at a broader level by quantifying the relative impact of different categories of specifications of interest (either alone or in interaction with one another).

Importantly, median effect sizes (and their accompanying distributions and variances) are influenced by the model choices included in a given SCA, and both multiverse underevaluation (i.e., omission of plausible, equivalent model choices and terms) and unrepresentativeness (i.e., inclusion of implausible model choices or terms) threatens the representativeness of SCA results. Representation, evaluation, and equivalence, however, depend on the focal relationships of interest and study goals. It is thus critical to establish for what purposes SCA is being used (e.g., data exploration, summary, and screening vs. confirmatory testing, causal effect estimation, and inferential robustness checks) and thereby what the median effect size and other associated results are intended to represent (e.g., indicators of the conditions under which stronger or weaker associations between broader constructs would be reported or observed vs. a parameter estimate of a causal relationship between specific variables, across all plausible specifications). In the present work, we use SCA for exploratory, summary, and screening purposes; thus, median effect sizes and other results are compared and evaluated to identify and summarize where the strongest and weakest relationships emerge between "control" and "well-being" constructs, broadly construed.

For SCA used toward other ends, effect size values and patterns may be directly considered through joint inferential testing, wherein one or more test statistics (e.g., median effect sizes, proportion of statistically significant results in predicted directions, aggregated *z*-values for each specification's *p*-value) are evaluated to determine their likelihood of occurrence if the true effect across specifications were zero. For non-experimental data, this requires specification curve bootstrapping (i.e., simulated resampling) and subsequent proportional comparison of test statistics from focal and bootstrapped samples. These analyses can be conducted for a specific subset of specification curves and associated results (e.g., for particular predictor operationalizations and median effect size estimates) or for the specification curve overall (i.e., median overall effect size considering all model specifications). Many challenges emerge in this process, including but not limited to: determining appropriate weights for inferential testing (i.e., as the specifications are neither equally plausible/viable nor independent), extracting *p*-values from a mixed-effects modeling framework, and selecting an interpretable, useful, and representative set of specifications to compare (i.e., based on an overall specification curve or separate curves for more focused investigation; e.g., Frey et al., 2021).

Given the exploratory focus of the present work, rather than provide inferential SCA interpretations, we focus on identifying patterns and effects of different conceptual and analytical decisions on observed relationships with the three result categories noted above and a discussion of gaps and limitations of SCA therefrom. This is also in keeping with potential issues of non-equivalence or varying types of equivalence across our specifications, for which it is recommended analyses be conducted exploratorily and with caution in interpreting statistical significance (see discussion in Del Giudice & Gangestad, 2021; Masur, 2021). We return to this gap in inferential statistical theory in SCA later, as it is a limitation of this approach that has gone under-discussed in the literature (cf. Semken & Rossell, 2022; Slez, 2019) and must be borne in mind when considering analytical approaches (SCA and others) to assess effect robustness or uncertainty across specifications in the aging literature moving forward.

In addition to the SCA results, we provide an interactive website (see https://cortrudolph.shinyapps.io/CONTROL_APP/), where readers can explore customize mixed-effects models with multiple additional predictors to investigate resulting model parameters, conduct dominance analyses, and consider model R^2 values. This site also permits readers to consider actual control-relevant demographics (i.e., age, gender, socioeconomic status) as predictors as well as test interactions between these variables and other forms of control in predicting well-being; in our SCA, in contrast, these actual control-relevant sociodemographics are considered as covariates, given their frequent treatment as such in the literature (e.g., Hamm et al., 2022).

3. Results

The SCA results suggest that both conceptual and analytical decisions have various effects on obtained results; as noted earlier, we provide detailed interpretation of the various results aging researchers may find to be of most interest in considering and reporting in their own work, as well as those components that speak most directly to our research questions and study goals (Table 5). Across all specifications, 523 (26.41 %) significant negative effects and 1160 (58.59 %) positive effects of control on well-being were observed; 297 effects, or 15.00 % of specifications, had 95 % confidence intervals including zero (i.e., $p >$ .05). The median effect of control predictors on well-being outcomes was small and positive, $\beta = 0.05$ ($b = 0.16$, median absolute deviation (MAD) = 0.51, $n_{median} = 6412$). Median observed effects across the control predictors and well-being outcomes were in line with the variables' valence, with all control predictor variables except for aspiration lowering (i.e., a form of enacted control; $\beta = -0.13$, $b = -0.82$, $MAD =$ 0.64, $n_{median} = 8765$) and perceived constraints (i.e., a form of perceived control; $\beta = -0.38$, $b = -0.90$, $MAD = 0.76$, $n_{median} = 8762$) returning positive median observed effects on well-being outcomes. Similarly, all well-being outcomes had observed median effects in expected directions, with each outcome except for chronic conditions ($\beta = -0.03$, $b = -0.17$, $MAD = 0.21$, $n_{median} = 6245$) and depression ($\beta = -0.04$, $b = -0.12$, $MAD = 0.18$, $n_{median} = 7623$) returning positive median effects. All configurations of included covariates returned uniformly small, positive median effects, as did the use of different subsets of data according to missingness (see Table 2). Table 2 provides a summary of additional median effects and descriptive statistics for each control predictor and well-being outcome operationalization in addition to other model specifications.

These results are corroborated by visual inspection of the specification curve and analytical choices plots (see Figs. 1–3), which in addition to displaying the occurrence of non-significant and significant negative and positive relationships between control and well-being also depict the effects observed with different configurations of covariates and data inclusion criteria. Specifically, Fig. 1 displays the specification curve and analytical choices plots together (as well as the number of observations upon which each specification was tested), whereas Fig. 2 presents the curve plot by itself to facilitate legibility. In the specification curve, each plotted point denotes an effect (i.e., a standardized regression coefficient) estimated in one of the model specifications. These specifications are ranked in order of magnitude, with color denoting their direction and significance (i.e., red indicating a significant negative effect, blue indicating a significant positive effect, and gray indicating a non-significant effect; each based on an assumed $\alpha = 0.05$).

The specification curve analysis entailed the simultaneous estimation of 1980 models, varying in their inclusion of 11 predictor and ten outcome variable operationalizations, covariates (i.e., with six possible configurations: no covariates; controlling for age, sex, SES, or data collection time lag; controlling for all covariates), and data completeness (i.e., with three possible data subsets: all data, participants with complete data across the three waves, participants with incomplete data across the three waves). Thus, the curve plot reflects 1980 standardized regression coefficients wherein a given operationalization of control (e.g., perceived constraints) predicts a given operationalization of well-being (e.g., depression) in a given data subset and with or without certain covariates simultaneously modeled.

Fig. 3 depicts the nature of each of these specifications, ranked in parallel with the specification curve itself and using the same color scheme described above. Specifically, each line denotes the inclusion of a particular analytical choice in a given specification, and the color of the line indicates the direction and statistical significance of the resulting effect size estimate (i.e., gray for non-significant; red and blue for significant in negative and positive directions, respectively). In short, this plot displays the particular model choices associated with each estimate in the specification curve, and the patterns visible here (e.g., of effect size significance, direction, extremity) can be interpreted visually alongside the quantitative metrics (i.e., median effects and descriptive statistics) already presented. In addition to the median values presented earlier (see Table 2), Fig. 4 provides an alternative way of visualizing these SCA results, presenting boxplots that reflect the distribution of effects associated with each specification choice. Each category of conceptual and analytical choice (e.g., operationalization, data subset) is assigned a different color, and each boxplot displays the median effect size estimate associated with a given choice and the dispersion of effects

Table 2
Summary of specification curve results: control-well-being effects.

Specification	Median β	Median b	Median absolute deviation (b)	Minimum effect (b)	Maximum effect (b)	Lower quartile (b)	Upper quartile (b)	N_{obs}
Overall	0.05	0.16	0.51	−1.86	2.23	−0.13	0.59	6412
Control predictor (GMC)								
Decision impact (A)	0.03	0.16	0.27	−0.29	0.75	−0.02	0.34	5852
Decision freedom (A)	0.03	0.18	0.31	−0.30	0.94	0.04	0.51	5852
Decision frequency (A)	0.03	0.11	0.20	−0.25	0.45	0.00	0.26	5852
Work structure (A)	0.04	0.20	0.30	−0.29	0.99	0.09	0.51	5852
Lowering aspirations (E)	−0.13	−0.82	0.64	−1.45	0.48	−0.96	−0.12	8765
Goal persistence (E)	0.22	1.15	1.13	−0.50	2.17	0.23	1.83	8766
Positive reappraisals (E)	0.22	1.04	0.96	−0.40	2.09	0.15	1.60	8769
Job decision authority (P)	0.10	0.06	0.05	−0.03	0.13	0.02	0.09	5939
Sense of control (P)	0.37	1.11	0.98	−0.65	2.23	0.20	1.60	8760
Perceived constraints (P)	−0.38	−0.90	0.76	−1.86	0.53	−1.34	−0.16	8762
Perceived mastery (P)	0.21	0.65	0.63	−0.36	1.33	0.12	1.04	8760
Well-being outcome								
Autonomy	0.03	0.22	0.79	−0.90	1.66	0.04	0.97	6400
Chronic conditions	−0.03	−0.17	0.21	−0.65	0.53	−0.29	−0.02	6245
Depression	−0.04	−0.12	0.18	−0.42	0.34	−0.24	0.01	7623
Environmental mastery	0.06	0.27	1.47	−1.86	2.23	0.09	1.54	6411
Life satisfaction	0.05	0.06	0.36	−0.43	0.62	0.00	0.40	6435
Personal growth	0.08	0.51	0.79	−1.22	2.09	0.12	1.52	6410
Physical health	0.06	0.12	0.09	−0.21	0.27	0.02	0.16	7620
Positive relations	0.06	0.36	0.69	−1.38	1.68	0.05	1.17	6412
Purpose in life	0.08	0.48	0.58	−1.45	1.37	0.10	0.88	6412
Self-acceptance	0.07	0.48	1.02	−1.71	2.08	0.11	1.68	6412
Covariates								
Age	0.06	0.19	0.58	−1.84	2.22	−0.16	0.68	8644
Time lag duration	0.06	0.21	0.55	−1.85	2.23	−0.14	0.63	6586
SES	0.03	0.11	0.39	−1.78	2.13	−0.11	0.45	7967
Sex	0.06	0.19	0.57	−1.85	2.22	−0.13	0.69	8644
All covariates	0.04	0.13	0.39	−1.76	2.14	−0.07	0.47	6066
No covariates	0.06	0.19	0.58	−1.86	2.23	−0.17	0.68	8644
Data subsets								
All data (n = 7180)	0.05	0.18	0.55	−1.56	2.08	−0.15	0.64	8770
Complete data (n = 769)	0.04	0.14	0.39	−1.86	2.23	−0.10	0.49	2307
Incomplete data (n = 6339)	0.06	0.18	0.59	−1.51	2.09	−0.16	0.71	6463

Note. N_{obs} = median number of observations. "GMC" = grand mean centered, "A" = actual control, "E" = enacted control, "P" = perceived control.

therefrom (including red dots for extreme/outlier values). This graphic also includes boxplots labeled "mixed_linear," which refers to the mixed-effects model tested and visually presents the median overall observed effect.

Considering these plots in greater detail, a number of patterns become apparent. First, there do not seem to be clear effects of either covariate inclusion or data subsetting on observed effects, with generally comparable and evenly distributed effect ranges depicted. The inclusion of SES as a covariate or all covariates appeared to result in a similar median effect very close to zero, while other covariate inclusion decisions resulted in moderately larger (yet still near-zero) median effects. Similarly, considering only complete data cases in analyses results in a slightly smaller median effect size (and a greater share of non-significant effects) than does the inclusion of data with missing values or all data, but these effects largely overlap.

In terms of predictor and outcome variable specifications, psychological and subjective well-being operationalizations have the most extreme and diffuse observed effects, while physical and mental health operationalizations manifested more concentrated effects. As noted earlier, depression and chronic conditions (unsurprisingly) were associated with a greater share of negative effects than were other outcome operationalizations. Of the subjective and psychological well-being outcomes considered, life satisfaction, environmental mastery, and autonomy were associated with more non-significant effects. Most of the non-significant effects observed across the well-being variable specifications occurred in models with actual control variables as predictors. Actual control variable predictors were associated with a greater share of non-significant effects when compared to the perceived and enacted control predictor specifications considered. In addition, actual control predictor variables were associated with less extreme negative and positive significant effects. Domain-general perceived control was associated with largely extreme and significant effects in both directions, whereas job-related perceived control had a narrower spread of effects. This pattern was true for enacted control predictors as well, though the range of effects observed for aspiration lowering was smaller than for goal persistence and positive reappraisals.

Considering variance explained across the full set of model specifications, results similarly suggest that operationalization decisions (and interactions therein) account for a much greater amount of variance than do other specification components (see Table 3, Fig. 5). Predictor operationalization was found to account for 49.29 % of observed variance, whereas the combination of particular predictor and outcome operationalizations accounts for an additional 48.18 % of variance. The remaining 2.53 % of variance is explained by outcome operationalization (1.25 %), residual error (1.13 %), interactions between outcome and predictor operationalizations and covariates (0.06 % and 0.04 %, respectively), covariate inclusion (0.03 %), and data subsetting decisions (0.02 %).

Variance was also decomposed across a subset of model specifications (n_{models} = 110) that only considered different combinations of predictor and outcome operationalizations. This subset was created to streamline the interpretation of results and focused on conceptual specification decisions, given their role in accounting for the preponderance of model variance across specifications. Within this subset of model specifications, each of the ten well-being outcomes were considered individually, and the predictor variable specification(s) associated with the highest and lowest model R^2 value for each outcome were evaluated (i.e., 20 predictor and outcome pairs total). Results of

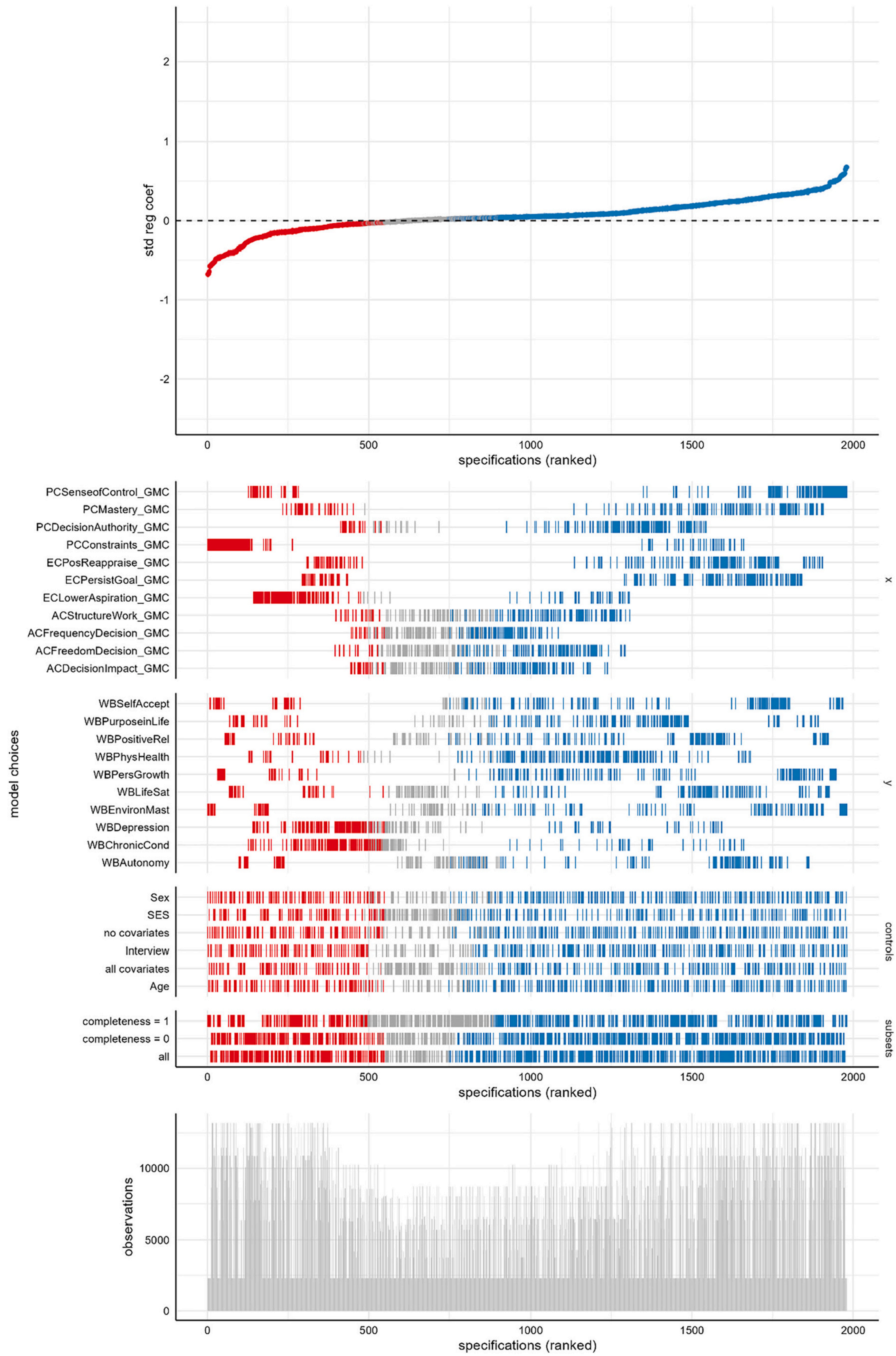

Fig. 1. Overall specification curve, specification decisions, and sample size plots.

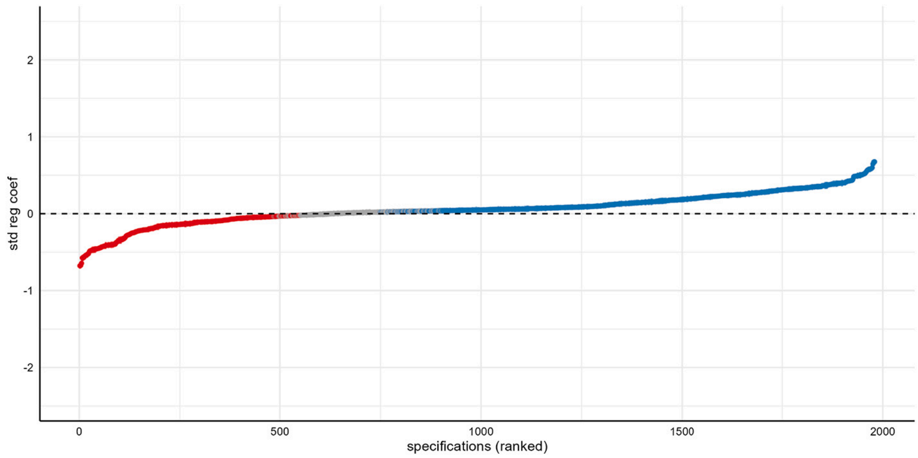

Fig. 2. Specification curve (N_{models} = 1980)
Note. "std reg coef" = standardized regression coefficient. Red denotes negative significant effect observed in a given specification, gray denotes non-significant effect, and blue denotes positive significant effect (α = 0.05). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

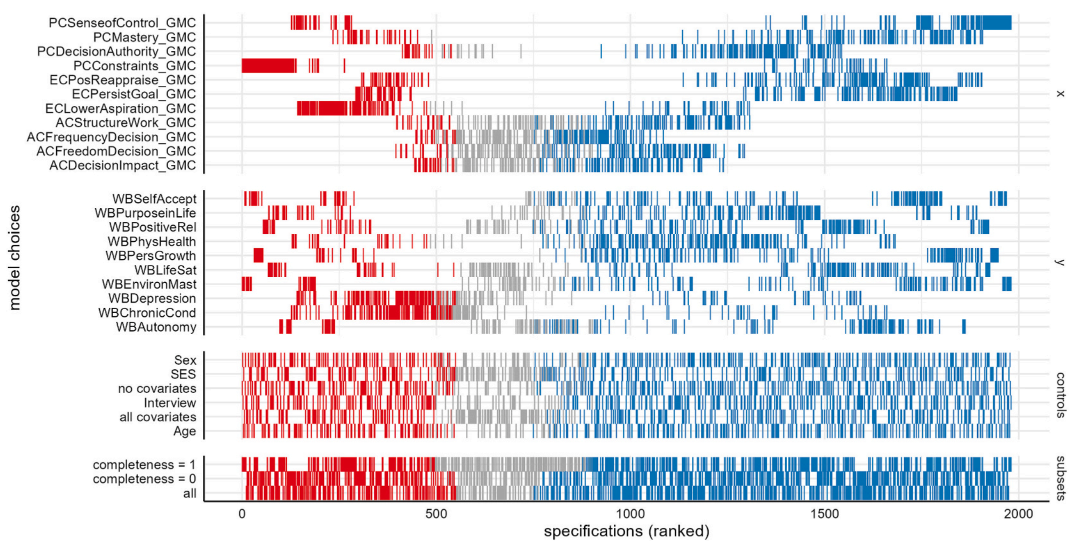

Fig. 3. Specification decision plot (N_{models} = 1980)
Note. "model choices" = conceptual and analytical specification decisions, "x" = control predictor operationalization, "y" = well-being outcome operationalization, "controls" = covariates included in model specification, "subsets" = data included in model specification ("all" = all data included (*n* = 7108); "completeness = 1" = only data with complete cases at composite level included (*n* = 769); "completeness = 0" = data with incomplete cases at composite level included (*n* = 6339)). Red denotes negative significant effect observed in a given specification, gray denotes non-significant effect, and blue denotes positive significant effect (α = 0.05). "GMC" = grand mean centered, "WB" = well-being. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

these analyses are presented in Table 4.

Of the models considering psychological well-being variables as outcomes, those with domain-general perceived control (and operationalized as a single variable, sense of control, rather than considered separately as mastery and constraints) as a predictor returned the highest R^2 values, while those with enacted control predictors (or an actual control predictor, work structure, in the case of personal growth) returned the lowest R^2 values. Additionally, for model specifications considering subjective well-being (life satisfaction) and more objective physical and mental health outcomes (depression, self-rated physical health, chronic conditions), sense of control again emerged as the predictor associated with the highest R^2 values. This was true in every case except for chronic conditions, for which the predictor choice of goal persistence (enacted control) returned the highest R^2 value. Forms of actual job control were predictors in the depression, physical health, and chronic conditions models with the lowest R^2 values. It is important to note, however, that the range of R^2 values observed was not very wide for any set of model specifications associated with a given outcome variable (e.g., R^2 ranged from 0.47 to 0.48 for models specified with autonomy as an outcome), and generally similar R^2 ranges were observed for each well-being outcome across predictor choices with the exception of depression (model R^2 ranging from 0.23 to 0.30).

As noted, some aspects of our research questions not best tested in SCA are available for interactive testing via a website created for this project (see https://cortrudolph.shinyapps.io/CONTROL_APP/). For example, interactions can be tested to consider age-conditional effects of certain forms of control on various well-being outcomes, or interactions between different types, levels, or domains of control (see Table 1). The relative importance and contributions of different forms (i.e., actual, perceived, enacted) and levels (i.e., between- and within-person) of control in predicting different well-being outcomes can be assessed as well, with or without covariates included. Mixed effects regression model parameters (i.e., random and fixed effects values, confidence intervals, and inferential test results), dominance analysis findings, model R-squared values, and plots (of fixed effects, of predicted well-being values at high and low levels of the moderator) can be generated with this website. We recommend using our specification curve findings, in combination with identified needs in theory and practice, as

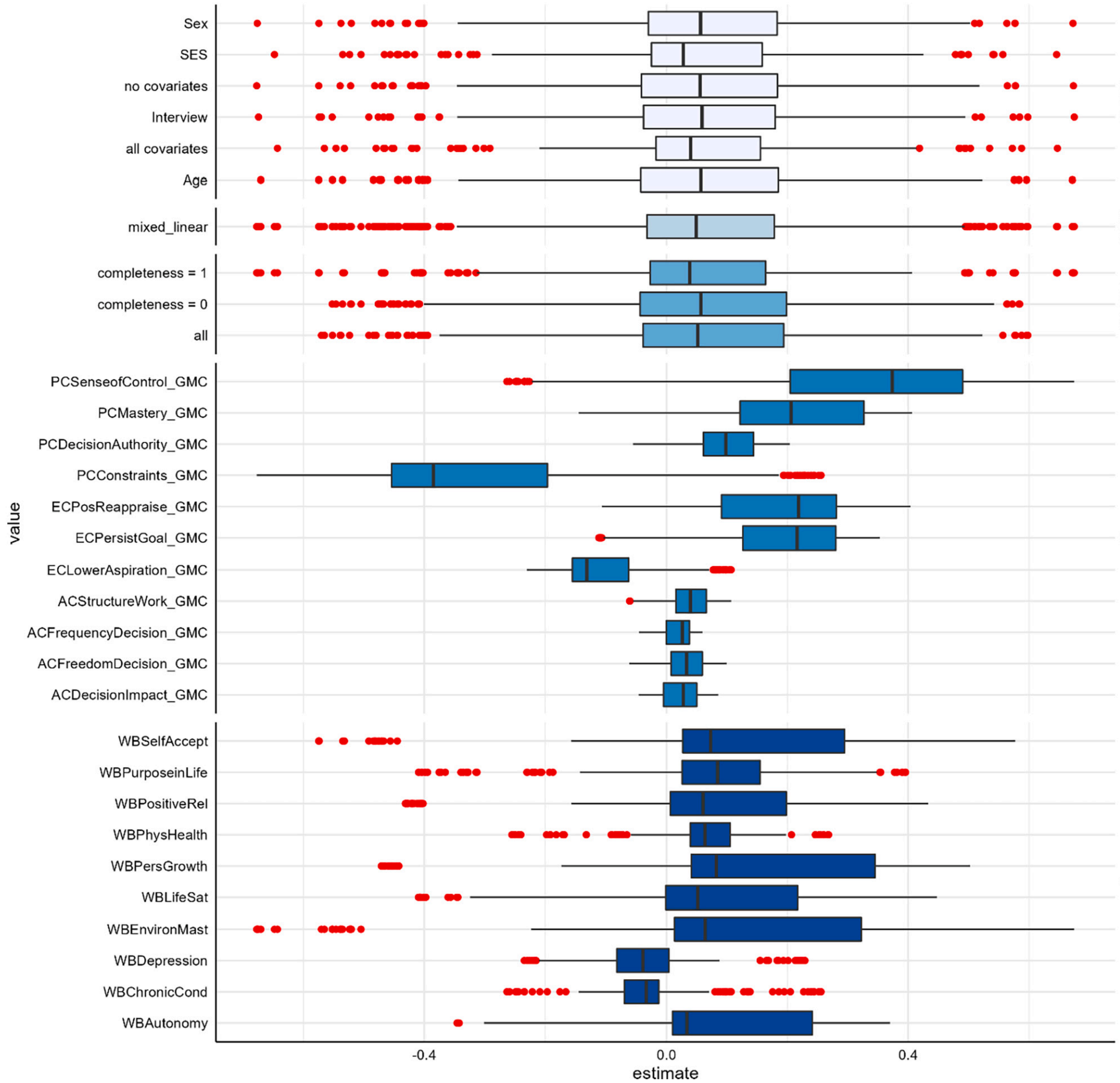

Fig. 4. Specification decision effect boxplots ($N_{models} = 1980$)
Note. "value" = specification decision, "estimate" = standardized regression coefficient, "controls" = covariates included in model specification, "model" = model type specification, "subsets" = data included in model specification ("all" = all data included ($n = 7108$); "completeness = 1" = only data with complete cases at composite level included ($n = 769$); "completeness = 0" = data with incomplete cases at composite level included ($n = 6339$)), "x" = control predictor operationalization, "y" = well-being outcome operationalization. Red dots indicate outlier values. "GMC" = grand mean centered, "WB" = well-being. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

a basis for conducting these tests (e.g., to explore when and for whom certain forms and domains of control are more or less adaptive, to assess the level at which types of control are most influential and for which types of well-being).

4. Discussion

As noted at the outset of this paper, control is generally construed as "good"—such that more control is better than less control; it is adaptive to possess, perceive, and exercise across the lifespan; and all of this holds true over time, across life domains, and in relation to various forms of well-being. However, these presentations lack nuance and provide little guidance to researchers seeking to understand specific, actionable mechanisms for improving well-being across the working adult lifespan. Particularly considering the centrality of work to activity, identity, livelihood, and health, there is a clear need to identify the types, levels, and domains of control most optimal for adult functioning in and outside of organizations. To move toward this goal, we must use existing resources at our disposal to better understand how our conceptual and analytical decisions (and discretion therewith) have shaped and continue to shape observed results and conclusions. The interpretation we provide next, in combination with the model testing resources provided in our appendix and interactive website, are intended to support future efforts to systematically consider various conceptual and analytical decision points—theoretical and arbitrary alike—in the aging, control, and work literature. We do so in two ways: first, by presenting findings and analytical resources that speak to the relative effects of certain decisions on observed control-well-being relationships using a

Table 3
Variance explained by model components in specification curve (N_{models} = 1980).

Model component	ICC	Variance explained (%)
Predictor × outcome	0.48	48.18
Predictor × covariate	0.00	0.04
Outcome × covariate	0.00	0.06
Predictor	0.49	49.29
Outcome	0.01	1.25
Covariates	0.00	0.03
Data subsets	0.00	0.02
Residual	0.00	1.13

Note. ICC = intraclass correlation coefficient. "x" indicates interaction between model components indicated (e.g., co-incidence of particular predictor and outcome pairs in specifications).

large, age-diverse dataset, and second, by providing a guide to and discussion of the strengths and limitations of using SCA toward different ends as a complement to additional theoretical, empirical, and practical work related to aging and adult development.

Regarding the first research question explored (i.e., the effects of variable operationalizations and types on observed relationships), our results indicate a few important points and distinctions. Theoretically consistent, statistically significant positive and negative effects were observed across all control and well-being categories and operationalizations. Still, the direction, spread, and magnitude of these effects differed widely, particularly when considering control and predictor variable operationalizations. Fittingly, predictor variable specifications and combinations of predictor and outcome variable specifications accounted for the lion's share of model variance across the specification curve (97.47 %). Outcome variable specifications and other model choices accounted for comparatively little variance. This suggests that predictor selection, and the pairing of particular predictors with outcome variables, was of most consequence here for the nature of the effects observed. Of course, this is a sensible and natural finding: one would certainly expect to observe variability in the degree to which certain predictors relate to given outcomes, whether for theoretical, methodological, or other reasons (e.g., different underlying causal paths). Researchers looking to adopt this method in their own work will need and want to interpret this class of findings, as it bears great informative potential in the assessment of specification robustness and effect variability. Whether considering a large set of predictor and outcome conceptualizations or operationalizations (i.e., as measured or as scored and analyzed) deemed reasonably comparable and valid within alternative causal models, or separately analyzing decisions deemed non-equivalent but worth exploring, parsing variance will prove useful for characterizing result robustness, comparing specifications within or across curves (as in the case of non-equivalent models or those of unknown equivalence; see discussion in Del Giudice & Gangestad, 2021), and informing interpretations. First, however, it is imperative that researchers establish their goals for using SCA and thereby how they will interpret their results (i.e., median effect size, distribution, variance). Based on various limitations in both the inferential statistical theory underlying SCA as well as computational limitations with current analytical packages, we recommend the use of SCA for exploratory screening purposes, as in the present work, while urging caution around its use for more causal and inferential purposes.

In the present worked example, we observed that types of control and well-being clearly matter for observed effects: perceived control as well as enacted control specifications returning a greater share of significant effects, and more extreme effects, than did specifications with objective job control as predictors. The domain and form of perceived control considered mattered as well, as domain-general perceived control, operationalized as a composite of perceived mastery and constraints, was associated with the highest magnitude effects in the positive direction and the highest model variance explained for almost all well-being outcomes. Still, perceived constraints were associated with the highest magnitude effects in the negative direction, and both perceived mastery and job-specific perceived control (i.e., perceived job decision authority) predicted well-being in both directions.

We also want to highlight that although actual control predictors were comparatively associated with less extreme and more non-significant effects, they still demonstrated significant predictive power in both directions across various well-being outcomes and specifications. This is perhaps even more impressive when reflecting on the nature of these data, which were from a completely separate, objective source (O*NET). This finding points to the need for further exploration of such forms of control alongside self-reported phenomena. Actual control-relevant demographics (age, sex, SES), which are often controlled for in organizational research, did not have any clear bearing on observed results when included or excluded from the covariate set. Rather than controlling for these factors, especially absent clear

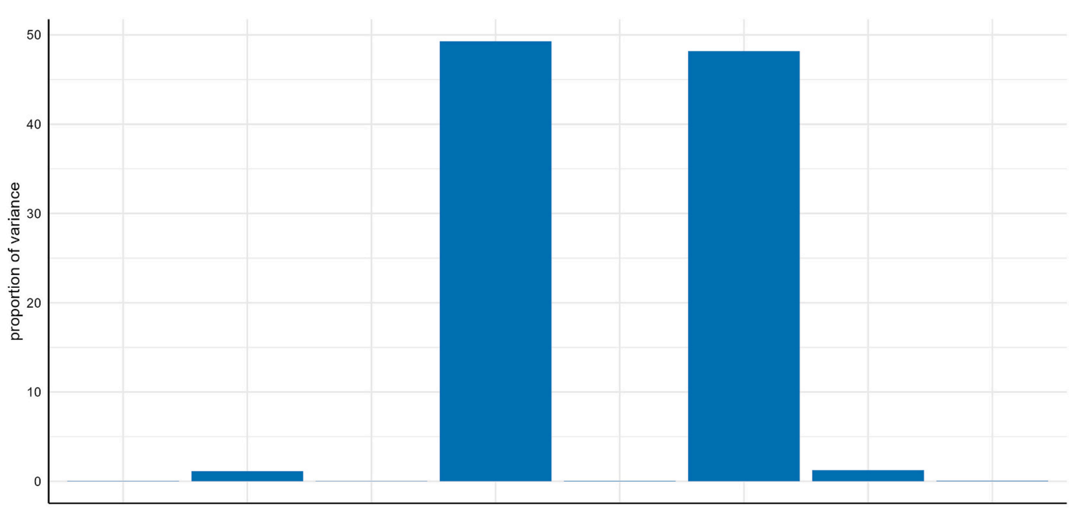

Fig. 5. Variance decomposition by model component across specifications (N_{models} = 1980)
Note. "proportion of variance" = R^2 associated with component of model specification (i.e., reflected as a whole number from 0 % to 50 %), "controls" = included covariates, "Residual" = residual variance, "subsets" = data inclusion, "x" = control predictor operationalization, "x:controls" = interaction of control predictor operationalization and included covariates, "x:y" = interaction of control predictor and well-being outcome operationalizations, "y" = wellbeing outcome operationalization, "y:controls" = interaction of well-being outcome operationalization and included covariates.

Table 4
Variance explained by control predictors in specification subset ($N_{models} = 110$).

Predictor (GMC)	Outcome	β	b	N_{obs}	R^2
Decision impact (A)	Depression	−0.00	−0.02	6076	0.23
Sense of control (P)	Depression	−0.18	−0.33	8647	0.30
Decision frequency (A)	Physical health	0.04	0.09	6074	0.46
Sense of control (P)	Physical health	0.18	0.18	8645	0.49
Decision freedom (A)	Chronic conditions	0.01	0.04	5977	0.51
Goal persistence (E)	Chronic conditions	−0.17	−0.38	8506	0.58
Goal persistence (E)	Life satisfaction	0.20	0.47	8646	0.56
Sense of control (P)	Life satisfaction	0.37	0.46	8647	0.60
Positive reappraisals (E)	Autonomy	0.24	1.23	8635	0.47
Sense of control (P)	Autonomy	0.33	1.03	8643	0.48
Lowering aspirations (E)	Purpose in life	−0.19	−1.18	8637	0.46
Sense of control (P)	Purpose in life	0.31	1.08	8645	0.49
Positive reappraisals (E)	Positive relations	0.23	1.47	8643	0.55
Sense of control (P)	Positive relations	0.41	1.60	8647	0.59
Lowering aspirations (E)	Self-acceptance	−0.14	−0.92	8637	0.57
Sense of control (P)	Self-acceptance	0.50	1.81	8644	0.62
Lowering aspirations (E)	Environmental mastery	−0.20	−1.21	8637	0.46
Sense of control (P)	Environmental mastery	0.59	1.94	8643	0.55
Work structure (A)	Personal growth	0.06	0.49	6068	0.49
Sense of control (P)	Personal growth	0.49	1.51	8643	0.55

Note. "GMC" = grand mean centered, "A" = actual control, "E" = enacted control, "P" = perceived control.

rationale for doing so (e.g., Bernerth & Aguinis, 2016) we recommend exploring them as substantive predictors or in interaction with various forms of control on our website.

When considering a subset of specifications varying only in their operationalization and combination of control and well-being, domain-general perceived control (i.e., sense of control, for nine of the ten well-being outcomes) and enacted control (i.e., goal persistence, in the case of life satisfaction) were specified in the models with the highest R^2 values. Actual (in four cases) and enacted control predictors (in six cases) were specified in the models with the lowest R^2 values for each well-being outcome. Still, R^2 values were all relatively large and did not vary much between the "lowest" and "highest" models, with a 0.09 difference in one case (environmental mastery). Considering outcomes, psychological and subjective well-being specifications generally produced a wider or more distributed volume of effects, while more objective physical and mental health specifications produced a more concentrated range of effects. Certain well-being variable choices, including physical health, personal growth, and self-acceptance, returned a much smaller share of non-significant results than did other well-being outcomes (e.g., life satisfaction, depression). These themes were corroborated across results considered (i.e., median effect sizes and ranges, data visualizations), underlining the importance of intentional selection and operationalization of control predictor variables, alone and in combination with relevant well-being outcomes. To this latter point, whereas most well-being variables were predicted in some way by perceived and enacted control, certain well-being outcomes (positively: psychological well-being, physical health; negatively: depression, chronic conditions) were also effectively predicted by actual control variables, even if to a less extreme extent. It seems reasonable to think that such findings have been overlooked or remained unpublished in the past, contributing to an unrepresentative and noncomprehensive literature.

In terms of evidence in answer to research questions two and three (i.e., the effects of longitudinal data analysis decisions and other reasonable specifications on observed results), our findings are mixed. Generally, neither the inclusion of particular covariate configurations nor data subsetting in specifications (i.e., applications of different data exclusion criteria) resulted in markedly different effects. Of those small differences observed, the consideration of only focal sample participants with complete data did result in a slightly larger share of non-significant results. It is worth exploring this finding further using sensitivity analyses in primary studies to determine if data subsetting changes one's focal conclusions. Other decisions, such as the inclusion of variable interactions or variable centering to isolate between- and within-person sources of variance, can be explored on our interactive website, https://cortrudolph.shinyapps.io/CONTROL_APP/. As with our SCA, there are an abundance of possible specifications to explore through this website, which we hope readers use to better understand both aging and work phenomena directly (e.g., by exploring interactions between chronological age and control variables at the between- and within-person levels of analysis) as well as the influence of modeling decisions on observed results.

4.1. Limitations

Our use of mixed-effects modeling and SCA was well justified for our study goals, but these methods have limitations that must be noted. First, some of the model specifications that we initially wanted to test were not feasible within the parameters of SCA as currently implemented (i.e., autocorrelative terms, additional approaches to modeling time and development), and multiple predictors could not be included at once in the model specifications, which barred us from simultaneously considering variable sets (e.g., within- and between person-level predictors). To address this latter issue, we chose to grand mean-center our predictor variables for the SCA and provide further parsed versions of these variables for testing on our interactive website.

Relatedly, although SCA is well geared to investigate the full "population" of reasonable model specifications, there are challenges associated with both defining this set of modeling decisions and interpreting the volume of specifications that result, even when employing the standard procedures described and utilized in our empirical demonstration. Outside of the bounds of an experimental paradigm, identifying and selecting a comprehensive and representative set of specifications can be a herculean task; to make matters more complicated, not all specifications can be assumed to be equally likely (or, put another way, arbitrary; Simonsohn et al., 2020). While weighting schemes can be implemented to offset this issue, determining appropriate weighting criteria is largely without precedent and itself adds new researcher "degrees of freedom" to the process. More work is needed in this area to address this limitation; in the meantime, researchers employing this method should take care to document and justify their specification-relevant goals (e.g., what they are trying to evaluate and estimate, whether they have confirmatory or exploratory aims) and decisions (e.g., selection, evaluation of equivalence) when reporting SCA findings, or opt for alternative approaches to addressing researcher "degrees of freedom" (e.g., pre-registration, data sharing, workflow and code transparency) without some of the same inferential gaps and risks (see also approaches in econometrics, ecology, and other risk analysis disciplines, e.g., multimodel ensembles and inference; Hoffmann et al., 2021).

Considering such risks more focally, we do not recommend SCA or other analytic approaches to assess specifications as tools for generating hypotheses post hoc or as alternatives to systematic or meta-analytic review procedures, however. SCA results do not attempt to tell us, definitively, the "true" importance of various constructs or magnitude of their relationships, and its seeming comprehensiveness and complexity do not transcend sampling and measurement error, researcher bias, or other artifacts and trappings of contemporary psychological research. Any given SCA is also only as robust as its specification procedures and equivalence judgments, and results must be interpreted in alignment with SCA's intended use and goals, the limitations of a given data collection, and the boundaries of research ethics and best practice. SCA results—ours and beyond—should not be used as a tool for identifying areas of statistical significance to capitalize upon through *p*-hacking and other questionable research practices (e.g., Banks et al., 2016), nor as definitive causal evidence. SCA is by nature reductive: it is intended to help us derive an understanding of how seemingly small decisions with operationalizations, coding, and model terms can translate into major discrepancies in observed results with a given dataset. It does not tell us where we can go "right" or "wrong." Rather, considering specification decisions can highlight where "right" and "wrong" are obscured, fuzzy, or variable; uncovering how this may have and continues to result in a fragmented and inconsistent literature and helping direct resources toward more transparent, replicable, and codified work moving forward.

4.2. Future directions and implications

We have various theoretical, empirical, and practical recommendations to address needs in the control, aging, and work literature and build upon the methods and findings presented herein. We base these recommendations in part on specific findings from our SCA as well as in the spirit of the needs identified at the outset of our paper (see Table 5). As an overarching recommendation, we call for scholars studying aging and adult development to consider specification decisions in their work, leveraging SCA for exploratory and summary purposes (given its various limitations) while carefully weighing SCA against other methods for confirmatory testing and inferential researcher "degrees of freedom" assessment. For these latter investigations, we recommend researchers make use of various approaches established across disciplines for handling uncertainty. To this end, Hoffmann et al. (2021) propose a solutions framework for reducing, reporting, integrating, and accepting uncertainty in research (i.e., across measures, methods, models, and parameters), and we recommend readers consult this guide in evaluating a variety of places and ways they can intervene in their own work. For example, when researchers have data on multiple measures of the same construct, structural equation modeling can be leveraged to attenuate measurement error and provide a formal assessment of uncertainty. More broadly, to overcome issues of researcher decision-making unaddressed by pre-registration and other open science practices, we echo others' calls for formal modeling (i.e., of predictions, theories, causal relationships), the specification of standardized and codeable (i.e., "machine-readable") hypotheses, and more nuanced recognition and embrace of the full spectrum of exploratory to confirmatory paradigms in the aging literature (Devezer et al., 2021; Rubin & Donkin, 2022; Scheel, 2022).

For all projects, we recommend that researchers clearly plan, describe, and ideally pre-register theoretically driven conceptual and analytical decisions, testing and reporting all reasonable alternatives and discussing why other specifications were deemed unreasonable, invalid, redundant, or nonequivalent (see Del Giudice & Gangestad, 2021). Our worked example, decision-making guidance and resources, and sample results interpretation are intended as a starting point for such efforts across the literature, as well as an impetus for more inferential statistical theory development and equivalence evaluation criteria in the multiverse analysis literature. In the meantime, SCA also stands to provide benefits in more exploratory settings, particularly to the extent it is used for identifying potential areas of results divergence or association variability, in relation to commonly selected variables and model decisions, within a given dataset or study (see further discussion in Flournoy et al., 2020; Kievit et al., 2022). A confirmatory study with the MIDUS data, even if pre-registered, still only provides one research team's perspective on conceptualizing, operationalizing, and analyzing control and well-being with the dataset (e.g., a study of job autonomy and chronic conditions among participants at Time 1, controlling for other factors), yet these specific results will still likely be generalized to, discussed at, and used as the basis for future studies at the broader "control" and "well-being" construct level. Using SCA in an exploratory capacity, then, can inform the interpretation of a given primary study's findings relative to other plausible specifications, as well as screen for areas in which associations are particularly strong (or weak) in a dataset.

Regarding other specific needs, which are based on our general findings as well as the issues motivating our empirical demonstration, we broadly recommend more work be done to specify the proposed interrelationships between various forms and types of control. Although there is an abundance of theory concerned with control, development, and well-being in and across life contexts, there is a paucity of formal, testable theory involving all categories of control (actual, perceived, enacted) with clearly specified mechanisms and processes (Rauvola & Rudolph, 2021; cf. Lachman et al., 2011). Theory should attempt to link specific forms of control more clearly to particular forms of well-being or other developmental outcomes (e.g., work performance, cognitive functioning, family health). Perennial questions about the relative importance of actual and perceived control (Robinson & Lachman, 2017) can be more formally framed and tested in such a framework as well. To this point, theorists seem to not know quite what to "do" with (i.e., where to locate) actual control in frameworks and models. We propose exploring the concept of one's "control context" in more diverse ways, reconsidering the underpinnings of control as a construct within politicized, biopsychosocial systems and paired with qualitative research to better understand individuals' experiences of agency and disempowerment as a function of various personal and contextual characteristics (see Rauvola & Rudolph, 2021). Indeed, there is nothing to say that we should continue solely relying on the same ways of defining and measuring control and well-being, particularly if we want to better understand heterogeneity and complexity in over-time processes.

We also recommend work to distill, reconsider, and reframe the large body of work that has already studied control in relation to work and aging. "Mixed results" in the literature can, potentially, be reconsidered as a product of conceptual and analytical decision-making in primary studies (e.g., predictor and/or outcome operationalizations), or these decisions in combination with other methodological and statistical artifacts. Systematic documentation and analysis of such decisions in the literature relative to observed findings (e.g., comprehensive reviews, meta-analyses) should prove valuable, both concerning the literature at large and focused on particular archival datasets upon which many projects have been conducted (see also Fisher et al., 2022). Moreover, heeding our calls for simultaneous consideration of multiple forms of control in a given theoretical model and empirical study will necessarily increase decision permutations and potential interactions. Careful attention to construct validity and methodological rigor will be as important as ever before. We encourage researchers to attend to these issues in the direct purpose and content of their studies (e.g., focusing on identifying "best practices" for measuring control) as well as through the use of dynamic (e.g., intensive "shortitudinal" studies, studies with varying time lags; Dormann & Griffin, 2015), multi-faceted (i.e., multisource and multi-method data collections), and structured (i.e., experimental or quasi-experimental) study paradigms. This work will need to be reflexive and "open" in order to truly move this area of the literature forward. This should entail providing rationale for study decisions as well as robustness checks and multiverse analyses of alternative specifications, considering different ways of modeling time or time lag variability (see discussion in Rauvola et al., 2021), or even crowd-sourcing analyses and reporting patterns of findings therefrom (Silberzahn et al., 2018).

From a practical standpoint, we present a few recommendations for both the improved design and implementation of large, longitudinal data collections, as well as the control-based mechanisms we consider when designing interventions (e.g., for improving adult functioning, occupational health). To the latter point, our findings support the importance of all forms of control for a wide array of health outcomes, and this importance holds up across other analytical decisions. Though we do not want to encourage over-interpretation of our particular findings, we recommend designing organizational and community interventions with each different type of control in mind and particular

Table 5
Study conclusions organized by needs and questions, goals, specifications, and findings.

Literature needs and research questions	Study goals	Analytic specifications	SCA findings and observations	Conclusions and recommendations
Simultaneous consideration of a range of domain-general and -specific forms of control in predicting well-being (***RQ1***)	Generate informative findings for the literature about modeling control and well-being phenomena	**SCA:** specifications included with varying control predictor and well-being outcome operationalizations **MEM site:** designed to specify multiple predictors and/or outcomes in one model, include interactions	Significant, theoretically-consistent positive and negative median effects across all control and well-being categories and operationalizations (Table 2, Fig. 3–4), with predictor variables and predictor-outcome combinations accounting for 97.47 % of model variance across curve (Table 3, Fig. 5) Perceived and enacted control specifications returned greater share of significant median effects, and more extreme effects, than specifications with actual job control as predictors (Table 2, Fig. 3–4) Sense of control and goal persistence were specified in models with the highest R^2 values, while actual and enacted control predictors were specified in the models with the lowest R^2 values for each well-being outcome (Table 4) Psychological and subjective well-being specifications produced wider distribution of median effects, while more objective physical and mental health specifications had more concentrated effects (Table 2, Fig. 3-4)	Predictor selection, and the pairing of particular predictors with outcome variables, are of most consequence for observed effects All types of control, even when comparatively different in terms of effect magnitude and extremity, have predictive power Less extreme findings for certain well-being outcomes or control predictors may have been overlooked or remained unpublished in the past Recommendations: More testable theory should be developed involving all categories of control and clearly specified mechanisms and processes linking them to specific forms of well-being or developmental outcomes; will require new ways of conceptualizing and measuring control, more dynamic methods, and a commitment to open science practices to systematically test To distill and reframe the mixed literature already considering aging, control, and work, reviews should comprehensively document and analyze conceptual and analytical decision-making in the aging and control literature Practical applications should continue to consider all forms of control and their ties to particular targeted well-being outcomes
Investigation of control and well-being phenomena, within and between subjects, over time (***RQ2***)	Generate informative findings for the literature about modeling control and well-being phenomena	**SCA:** models specified within mixed-effects framework, with random effect for each participant **MEM site:** designed to include predictors at within- and/or between-person levels, account for timing variables and interactions	Observed specification curve results accounted for data non-independence (nesting over time) Site can be used to generate mixed effects regression model parameters, dominance analysis findings, model R-squared values, and plots (of fixed effects, interactions)	Recommendations: Research is needed exploring whether different well-being outcomes or types of control have distinct trajectories or interactions over time, and accounting for inter- and intraindividual variability in these studies (and different ways of modeling time as well as intra- and interindividual variability therein) can be accomplished with multilevel SCA or other methods
Evaluation of model specification decisions' bearing on observed results (***RQ1, 2, & 3***)	Generate informative findings for the literature about modeling control and well-being phenomena Provide a structured example of and guidance on how future aging research can identify and evaluate viable model specifications	**SCA:** specifications included with varying sets of common covariates and data subsetting rules **MEM site:** designed to simultaneously consider variable operationalizations and levels, covariates, interactions, etc.	Neither particular covariate configurations nor data subsetting in specifications resulted in markedly different median effects (Table 2, Fig. 3–4) or notable variance in models (Table 3, Fig. 5) Code and methodological/analytical guidance can be used to apply SCA or other analytic methods to additional research areas	Findings and observed patterns robust to alternative covariate inclusion and data subset specifications Recommendations: Theoretically driven analytical decisions (e.g., covariate inclusion, assumptions about missing data patterns) should be clearly planned, described, and ideally pre-registered, with all reasonable alternative tested and reported and specifications deemed unreasonable, invalid, or redundant discussed Considering specifications from the outset of studies, whether with SCA or other tools suited to given purposes, can help better identify and subsequently avoid arbitrariness across stages of the (applied) research process and allow for more representative and nuanced data collections, findings, and interventions

Note. "RQ" = Research Question. "SCA" = specification curve analysis. "MEM" = mixed-effects modeling. "Tab." = table. "Fig." = figure.

well-being outcomes specified as targets (see examples in Mallers et al., 2014; Robinson & Lachman, 2017). It is worth exploring, too, whether different well-being outcomes and/or types of control have distinct trajectories or interactions over time, which is an area ripe for investigation in intervention follow-up studies. For example, the magnitude of different forms of control on well-being could well differ over time, with perceived control serving as a more proximal predictor than the more distal (yet still important) actual control someone possesses at work. Accounting for inter- and intraindividual variability in our research and practice will be paramount, the importance and value of which we demonstrate with our work as well.

We also want to emphasize the potential that attention to model specification decision-making holds for guiding and improving large-scale, resource-intensive studies of adult development and interventions therein. By enumerating and evaluating full specification spaces and identifying the (non)equivalence of different choices therein, we can better identify arbitrariness across various stages of the applied research process, and, in turn, distinguish those areas where decisions align with theory and lived experiences from those where decisions serve to divide, reduce, or even misrepresent. In multi-institutional research endeavors such as MIDUS, seemingly small decisions regarding response options, variable (re)coding, and missing data treatment (among others) stand to have profound effects on results and the communities in which findings are used for policy and practice. For example, MIDUS data have been collected to focus on (assigned) sex rather than gender or gender identity and treat this factor as a binary variable; such decisions ignore and obscure the experiences of individuals outside of this binary distinction, and they ultimately remove important variability and nuance from our work. Similar issues emerge for seemingly "straightforward" focal variables such as occupation and health status as well, which deserve careful and inclusive design considerations such that meaningful variance is not discarded before it can even be detected. Diversity in adult development and in relation to work must be captured, and done in an intersectional, evidence-based way (Rauvola & Rudolph, 2020; see also Andrea et al., 2022; Gilmore-Bykovskyi et al., 2022; Katz & Calasanti, 2015).

5. Conclusion

We noted three areas in the control, aging, and work literature in need of further attention at the outset of this paper, including the needs for (1) simultaneous consideration of various domain-general and –specific forms of control in predicting well-being outcomes, (2) investigation of these phenomena within- and between-person over time, and (3) evaluation of how our model specification decisions affect our results and conclusions. The present work and associated results and resources address each of these areas, generating informative findings for the literature about modeling control and well-being phenomena and providing a structured example of how to identify and evaluate viable model specifications in future work with different goals. In the process, we underscore the importance of various types, forms, and domains of control for a range of well-being outcomes in an age-diverse, employed sample over approximately two decades of life, and we highlight areas in need of further investigation, particularly through conceptual and analytical decision enumeration and assessment, to move aging research forward. As such, we call attention, both directly (through our findings) and in spirit (through our methodological guidance and empirical demonstration), to the potential weight and importance of each specification decision—to the arbitrariness and agency we enable, accept, and benefit from in the pursuit of statistical significance. It is only fitting that, to improve the study of control, we must better exercise our control over the research design and analysis process. Indeed, if we want to expand our knowledge of control's effects on adult development in and outside of work, there is great need for more transparency around and attention to how we shape our results, field, and society in turn.

Declaration of competing interest

The authors have no conflicts of interest to report.

Data availability

Data and code are linked in the manuscript

References

Abraham, J. D., & Hansson, R. O. (1996). Gender differences in the usefulness of goal-directed coping for middle-aged and older workers. *Journal of Applied Social Psychology, 26*, 657–669. https://doi.org/10.1111/j.1559-1816.1996.tb02737.x

Agrigoroaei, S., & Lachman, M. E. (2010). Personal control and aging: How beliefs and expectations matter. In J. C. Cavanaugh, C. K. Cavanaugh, J. Berry, & R. West (Eds.), *1. Aging in America* (pp. 177–201). Praeger/ABC-CLIO. Psychological aspects.

Andrea, S. B., Eisenberg-Guyot, J., Oddo, V. M., Peckham, T., Jacoby, D., & Hajat, A. (2022). Beyond hours worked and dollars earned: Multidimensional EQ, retirement trajectories and health in later life. *Work, Aging and Retirement, 8*, 51–73. https://doi.org/10.1093/workar/waab012

Athey, S., & Imbens, G. (2015). A measure of robustness to misspecification. *American Economic Review, 105*, 476–480. https://doi.org/10.1257/aer.p20151020

Banks, G. C., Rogelberg, S. G., Woznyj, H. M., Landis, R. S., & Rupp, D. E. (2016). Evidence on questionable research practices: The good, the bad, and the ugly. *Journal of Business and Psychology, 31*, 323–338. https://doi.org/10.1007/s10869-016-9456-7

Barlow, M. A., Wrosch, C., Hamm, J., Sacher, T., Miller, G. E., & Kunzmann, U. (2022). Discrete negative emotions and goal disengagement in older adulthood: Context effects and associations with emotional well-being. *Emotion, 22*, 1583–1594. https://doi.org/10.1037/emo0001091

Beatty, J. E., & McGonagle, A. K. (2018). Chronic health conditions and work identity from a lifespan development frame. In S. Werth, & C. Brownlow (Eds.), *Work and identity* (pp. 9–22). https://doi.org/10.1007/978-3-319-73936-6_2

Bernerth, J. B., & Aguinis, H. (2016). A critical review and best-practice recommendations for control variable usage. *Personnel Psychology, 69*, 229–283. https://doi.org/10.1111/peps.12103

Blair, S. E. (2000). The centrality of occupation during life transitions. *British Journal of Occupational Therapy, 63*, 231–237.

Bobak, M., Pikhart, H., Hertzman, C., Rose, R., & Marmot, M. (1998). Socioeconomic factors, perceived control and self-reported health in Russia: A cross-sectional survey. *Social Science & Medicine, 47*, 269–279. https://doi.org/10.1016/s0277-9536(98)00095-1

Brandstädter, J., & Renner, G. (1990). Tenacious goal pursuit and flexible goal adjustment: Explication and age-related analysis of assimilative and accommodative strategies of coping. *Psychology and Aging, 5*, 58–67. https://doi.org/10.1037/0882-7974.5.1.58

Brim, O. G., Baltes, P. B., Bumpass, L. L., Cleary, P. D., Featherman, D. L., Hazzard, W. R. Shweder, R. A., … (2019). *Midlife in the United States (MIDUS 1), 1995–1996*. Ann Arbor, MI: Inter-university Consortium for Political and Social Research. https://doi.org/10.3886/ICPSR02760.v14

Broadbent, J., de Quadros-Wander, S., & McGillivray, J. A. (2014). Perceived control's influence on wellbeing in residential care versus community dwelling older adults. *Journal of Happiness Studies, 15*, 845–855. https://doi.org/10.1007/s10902-013-9452-9

Chipperfield, J. G., Hamm, J. M., Perry, R. P., & Ruthig, J. C. (2017). Perspectives on studying perceived control in the twenty-first century. In M. D. Robinson, & M. Eid (Eds.), *The happy mind: Cognitive contributions to well-being* (pp. 215–233). https://doi.org/10.1007/978-3-319-58763-9_12

Del Giudice, M., & Gangestad, S. W. (2021). A traveler's guide to the multiverse: Promises, pitfalls, and a framework for the evaluation of analytic decisions. *Advances in Methods and Practices in Psychological Science, 4*. https://doi.org/10.1177/2515245920954925

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands–resources model of burnout. *Journal of Applied Psychology, 86*, 499–512. https://doi.org/10.1037/0021-9010.86.3.499

Devezer, B., Navarro, D. J., Vandekerckhove, J., & Ozge Buzbas, E. (2021). The case for formal methodology in scientific reform. *Royal Society Open Science, 8*, Article 200805. https://doi.org/10.1098/rsos.200805

Dormann, C., & Griffin, M. A. (2015). Optimal time lags in panel studies. *Psychological Methods, 20*, 489–505. https://doi.org/10.1037/met0000041

Drewelies, J., Koffer, R. E., Ram, N., Almeida, D. M., & Gerstorf, D. (2019). Control diversity: How across-domain control beliefs are associated with daily negative affect and differ with age. *Psychology and Aging, 34*, 625–639. https://doi.org/10.1037/pag0000366

Drewelies, J., Schade, H., Hülür, G., Hoppmann, C. A., Ram, N., & Gerstorf, D. (2020). The more we are in control, the merrier? Partner perceived control and negative

affect in the daily lives of older couples. *The Journals of Gerontology: Series B, 75*, 338–348. https://doi.org/10.1093/geronb/gby009
Fisher, G. G., Barnes-Farrell, J. L., Beckel, J. L., & Shultz, K. S. (2022). Using archival data to research age and work. In H. Zacher, & C. W. Rudolph (Eds.), *Age and work: Advances in theory, methods, and practice*.
Flournoy, J. C., Vijayakumar, N., Cheng, T. W., Cosme, D., Flannery, J. E., & Pfeifer, J. H. (2020). Improving practices and inferences in developmental cognitive neuroscience. *Developmental Cognitive Neuroscience, 45*, Article 100807. https://doi.org/10.1016/j.dcn.2020.100807
Frey, R., Richter, D., Schupp, J., Hertwig, R., & Mata, R. (2021). Identifying robust correlates of risk preference: A systematic approach using specification curve analysis. *Journal of Personality and Social Psychology, 120*, 538–557. https://doi.org/10.1037/pspp0000287
Gerstorf, D., Röcke, C., & Lachman, M. E. (2010). Antecedent–consequent relations of perceived control to health and social support: Longitudinal evidence for between-domain associations across adulthood. *The Journals of Gerontology: Series B, 66*, 61–71. https://doi.org/10.1093/geronb/gbq077
Gilmore-Bykovskyi, A., Croff, R., Glover, C. M., Jackson, J. D., Resendez, J., Perez, A., Zuelsdorff, M., Green-Harris, G., & Manly, J. J. (2022). Traversing the aging research and health equity divide: Toward intersectional frameworks of research justice and participation. *The Gerontologist, 62*, 711–720. https://doi.org/10.1093/geront/gnab107
Gruenewald, T. L., Karlamangla, A. S., Hu, P., Stein-Merkin, S., Crandall, C., Koretz, B., & Seeman, T. E. (2012). History of socioeconomic disadvantage and allostatic load in later life. *Social Science & Medicine, 74*, 75–83. https://doi.org/10.1016/j.socscimed.2011.09.037
Grümer, S., Silbereisen, R. K., & Heckhausen, J. (2013). Subjective well-being in times of social change: Congruence of control strategies and perceived control. *International Journal of Psychology, 48*, 1267–1283. https://doi.org/10.1080/00207594.2012.744839
Haase, C. M., Heckhausen, J., & Silbereisen, R. K. (2012). The interplay of occupational motivation and well-being during the transition from university to work. *Developmental Psychology, 48*, 1739–1751. https://doi.org/10.1037/a0026641
Hamm, J. M., Chipperfield, J. G., Perry, R. P., Parker, P. C., & Heckhausen, J. (2017). Tenacious self-reliance in health maintenance may jeopardize late life survival. *Psychology and Aging, 32*, 628–635. https://doi.org/10.1037/pag0000201
Hamm, J. M., Tan, J. X., Barlow, M. A., Delaney, R. L., & Duggan, K. A. (2022). Goal adjustment capacities in uncontrollable life circumstances: Benefits for psychological well-being during COVID-19. *Motivation and Emotion, 46*, 319–335. https://doi.org/10.1007/s11031-022-09941-6
Hamm, J. M., Wrosch, C., Barlow, M. A., & Kunzmann, U. (2021). A tale of two emotions: The diverging salience and health consequences of calmness and excitement in old age. *Psychology and Aging, 36*, 626–641. https://doi.org/10.1037/pag0000512
Heckhausen, J., Brandstätter, V., Fishbach, A., Freund, A. M., Lachman, M. E., & Robert, P. (2021). Goal changes and healthy aging. *The Journals of Gerontology: Series B, 76*, S105–S114. https://doi.org/10.1093/geronb/gbab038
Heckhausen, J., Wrosch, C., & Schulz, R. (2010). A motivational theory of life-span development. *Psychological Review, 117*, 32–60. https://doi.org/10.1037/a0017668
Heckhausen, J., Wrosch, C., & Schulz, R. (2019). Agency and motivation in adulthood and old age. *Annual Review of Psychology, 70*, 191–217. https://doi.org/10.1146/annurev-psych-010418- 103043
Heyl, V., Wahl, H.-W., & Mollenkopft, H. (2007). Affective well-being in old age: The role of tenacious goal pursuit and flexible goal adjustment. *European Psychologist, 12*, 119–129. https://doi.org/10.1027/1016-9040.12.2.119
Hill, P. L., & Stine-Morrow, E. A. (2022). Introduction to the special issue on transparency, replicability, and discovery in the psychological science of adult development and aging. *Psychology and Aging, 37*, 6–9. https://doi.org/10.1037/pag0000673
Hofer, S. M., & Piccinin, A. M. (2010). Toward an integrative science of life-span development and aging. *Journals of Gerontology: Series B, 65*, 269–278. https://doi.org/10.1093/geronb/gbq017
Hoffmann, S., Schönbrodt, F., Elsas, R., Wilson, R., Strasser, U., & Boulesteix, A. L. (2021). The multiplicity of analysis strategies jeopardizes replicability: Lessons learned across disciplines. *Royal Society Open Science, 8*, Article 201925. https://doi.org/10.1098/rsos.201925
Hoppmann, C. A., & Klumb, P. L. (2012). Daily management of work and family goals in employed parents. *Journal of Vocational Behavior, 81*, 191–198. https://doi.org/10.1016/j.jvb.2012.07.001
Infurna, F. J., Gerstorf, D., & Zarit, S. H. (2011). Examining dynamic links between perceived control and health: Longitudinal evidence for differential effects in midlife and old age. *Developmental Psychology, 47*, 9–18. https://doi.org/10.1037/a0021022
Infurna, F. J., Ram, N., & Gerstorf, D. (2013). Level and change in perceived control predict 19-year mortality: Findings from the americans' changing lives study. *Developmental Psychology, 49*, 1833–1847. https://doi.org/10.1037/a0031041
Isaacowitz, D. M., & Lind, M. (2019). Open science is for aging research, too. *InnovationAging, 3*, igz028. https://doi.org/10.1093/geroni/igz028
Kanfer, R., Beier, M. E., & Ackerman, P. L. (2013). Understanding work motivation in later adulthood: Toward an organizing framework. *European Journal of Work and Organizational Psychology, 22*, 253–264. https://doi.org/10.1080/1359432X.2012.734298
Karasek, R., Baker, D., Marxer, F., Ahlbom, A., & Theorell, T. (1981). Job decision latitude, job demands, and cardiovascular disease: A prospective study of Swedish men. *American Journal of Public Health, 71*, 694–705. https://doi.org/10.2105/ajph.71.7.694
Karasek, R., & Theorell, T. (1990). *Healthy work: Stress, productivity, and the reconstruction of working life*. New York, NY, US: Basic Books.
Katz, S., & Calasanti, T. (2015). Critical perspectives on successful aging: Does it "appeal more than it illuminates"? *The Gerontologist, 55*, 26–33. https://doi.org/10.1093/geront/gnu027
Kessler, R. C., Andrews, G., Mroczek, D., Ustun, B., & Wittchen, H. U. (1998). The World Health Organization composite international diagnostic interview short-form (CIDI-SF). *International Journal of Methods in Psychiatric Research, 7*, 171–185. https://doi.org/10.1002/mpr.47
Kievit, R. A., McCormick, E. M., Fuhrmann, D., Deserno, M. K., & Orben, A. (2022). Using large, publicly available data sets to study adolescent development: Opportunities and challenges. *Current Opinion in Psychology, 44*, 303–308. https://doi.org/10.1016/j.copsyc.2021.10.003
Knudsen, H. K., Ducharme, L. J., & Roman, P. M. (2007). Job stress and poor sleep quality: Data from an American sample of full-time workers. *Social Science & Medicine, 64*, 1997–2007. https://doi.org/10.1016/j.socscimed.2007.02.020
Koffer, R., Drewelies, J., Almeida, D. M., Conroy, D. E., Pincus, A. L., Gerstorf, D., & Ram, N. (2019). The role of general and daily control beliefs for affective stressor-reactivity across adulthood and old age. *The Journals of Gerontology: Series B, 74*, 242–253. https://doi.org/10.1093/geronb/gbx055
Körner, A., Reitzle, M., & Silbereisen, R. K. (2012). Work-related demands and life satisfaction: The effects of engagement and disengagement among employed and long-term unemployed people. *Journal of Vocational Behavior, 80*, 187–196. https://doi.org/10.1016/j.jvb.2011.05.004
Lachman, M. E., Agrigoroaei, S., & Rickenbach, E. H. (2015). Making sense of control: Change and consequences. In R. Scott, & S. Kosslyn (Eds.), *Emerging trends in the social and behavioral sciences* (pp. 1–16). https://doi.org/10.1002/9781118900772.etrds0209
Lachman, M. E., & Burack, O. R. (1993). Planning and control processes across the life span: An overview. *International Journal of Behavioral Development, 16*, 131–143. https://doi.org/10.1177/016502549301600203
Lachman, M. E., Neupert, S. D., & Agrigoroaei, S. (2011). The relevance of control beliefs for health and aging. In K. W. Schaie, & S. L. Willis (Eds.), *Handbook of the psychology of aging* (pp. 175–190). https://doi.org/10.1016/b978-0-12-380882-0.00011-5
Lachman, M. E., & Weaver, S. L. (1998a). Sociodemographic variations in the sense of control by domain: Findings from the MacArthur studies of midlife. *Psychology and Aging, 13*, 553–562. https://doi.org/10.1037/0882-7974.13.4.553
Lachman, M. E., & Weaver, S. L. (1998b). The sense of control as a moderator of social class differences in health and well-being. *Journal of Personality and Social Psychology, 74*, 763–773. https://doi.org/10.1037/0022-3514.74.3.763
Lang, F. R., & Heckhausen, J. (2001). Perceived control over development and subjective well-being: Differential benefits across adulthood. *Journal of Personality and Social Psychology, 81*, 509–523. https://doi.org/10.1037/0022-3514.81.3.509
Langer, E. (1979). The illusion of incompetence. In L. Perlmutter, & R. Monty (Eds.), *Choice and perceived control* (pp. 301–313). Hillsdale, NJ: Erlbaum.
Leamer, E. E. (1983). Let's take the con out of econometrics. *The American Economic Review, 73*, 31–43.
Liu, M., McGonagle, A. K., & Fisher, G. G. (2018). Sense of control, job stressors, and well-being: Inter-relations and reciprocal effects among older U.S. workers. *Work, Aging and Retirement, 4*, 96–107. https://doi.org/10.1093/workar/waw035
Lubben, J., & Gironda, M. (2003). Centrality of social ties to the health and well-being of older adults. In B. Berkman, & L. Harootyan (Eds.), *Social work and health care in an aging world* (pp. 319–350). New York, NY: Springer.
Mallers, M. H., Claver, M., & Lares, L. A. (2014). Perceived control in the lives of older adults: The influence of langer and Rodin's work on gerontological theory, policy, and practice. *The Gerontologist, 54*, 67–74. https://doi.org/10.1093/geront/gnt051
Masur, P. K. (2021). Understanding the effects of conceptual and analytical choices on 'finding' the privacy paradox: A specification curve analysis of large-scale survey data. *Information, Communication & Society, 1–19*. https://doi.org/10.1080/1369118X.2021.1963460
Masur, P. K., & Scharkow, M. (2020). specr: Conducting and visualizing specification curve analyses. Available from https://CRAN.R-project.org/package=specr.
McGonagle, A. K., Fisher, G. G., Barnes-Farrell, J. L., & Grosch, J. W. (2015). Individual and work factors related to perceived work ability and labor force outcomes. *Journal of Applied Psychology, 100*, 376–398. https://doi.org/10.1037/a0037974
National Center for O*NET Development. (2019). O*NET 23.3 Database. O*NET Resource Center. Retrieved from https://www.onetcenter.org/database.html.
Ng, T. W., & Feldman, D. C. (2015). The moderating effects of age in the relationships of job autonomy to work outcomes. *Work, Aging and Retirement, 1*, 64–78. https://doi.org/10.1093/workar/wau003
Ng, T. W. H., Sorenson, K. L., & Eby, L. T. (2006). Locus of control at work: A meta-analysis. *Journal of Organizational Behavior, 27*, 1057–1087. https://doi.org/10.1002/job.416
Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behaviour, 3*, 173–182. https://doi.org/10.1038/s41562-018-0506-1
Prenda, K. M., & Lachman, M. E. (2001). Planning for the future: A life management strategy for increasing control and life satisfaction in adulthood. *Psychology and Aging, 16*, 206–216. https://doi.org/10.1037/0882-7974.16.2.206
Rauvola, R. S., & Rudolph, C. W. (2020). On the limits of agency for successful aging at work. *Industrial and Organizational Psychology: Perspectives on Science and Practice, 13*, 383–387. https://doi.org/10.1017/iop.2020.61
Rauvola, R. S., & Rudolph, C. W. (2021). Control at work: An integrative, lifespan-informed review. *Work, Aging & Retirement.*. https://doi.org/10.1093/workar/waab015
Rauvola, R. S., Rudolph, C. W., & Zacher, H. (2021). Handling time in contemporary occupational stress & well-being research: Considerations, examples, and recommendations. In P. D. Harms, P. L. Perrewé, & C.-H. D. Chang (Eds.), *19*.

Examining and exploring the shifting nature of occupational stress and well-being (pp. 105–135). https://doi.org/10.1108/S1479-355520210000019006. Research in Occupational Stress and Well Being.

Robinson, S. A., & Lachman, M. E. (2017). Perceived control and aging: A mini-review and directions for future research. *Gerontology, 63*, 435–442. https://doi.org/10.1159/000468540

Rodin, J. (1986). Aging and health: Effects of the sense of control. *Science, 233*, 1271–1276. https://doi.org/10.1126/science.3749877

Rubin, M., & Donkin, C. (2022). Exploratory hypothesis tests can be more compelling than confirmatory hypothesis tests. *Philosophical Psychology, 1–29*. https://doi.org/10.1080/09515089.2022.2113771

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology, 57*, 1069–1081. https://doi.org/10.1037//0022-3514.57.6.1069

Scheel, A. M. (2022). Why most psychological research findings are not even wrong. *Infant and Child Development, 31*, Article e2295. https://doi.org/10.1002/icd.2295

Schulz, R., & Heckhausen, J. (1996). A life span model of successful aging. *American Psychologist, 51*, 702–714. https://doi.org/10.1037/0003-066X.51.7.702

Schulz, R., & Heckhausen, J. (1999). Aging, culture and control: Setting a new research agenda. *The Journals of Gerontology: Series B, 54*, 139–145. https://doi.org/10.1093/geronb/54b.3.p139

Semken, C., & Rossell, D. (2022). *Specification analysis for technology use and teenager well-being: Statistical validity and a Bayesian proposal*. https://doi.org/10.48550/arXiv.2201.05381

Shane, J., & Heckhausen, J. (2012). Motivational self-regulation in the work domain: Congruence of individuals' control striving and the control potential in their developmental ecologies. *Research in Human Development, 9*, 337–357. https://doi.org/10.1080/15427609.2012.729918

Shane, J., & Heckhausen, J. (2016). Optimized engagement across life domains in adult development: Balancing diversity and interdomain consequences. *Research in Human Development, 13*, 280–296. https://doi.org/10.1080/15427609.2016.1234308

Silberzahn, R., Uhlmann, E. L., Martin, D. P., Anselmi, P., Aust, F., Awtrey, E. Nosek, B. A., … (2018). Many analysts, one data set: Making transparent how variations in analytic choices affect results. *Advances in Methods and Practices in Psychological Science, 1*, 337–356. https://doi.org/10.1177/2515245917747646

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science, 22*, 1359–1366. https://doi.org/10.1177/0956797611417632

Simonsohn, U., Simmons, J. P., & Nelson, L. D. (2020). Specification curve analysis. *Nature humanBehaviour, 4*, 1208–1214. https://doi.org/10.1038/s41562-020-0912-z

Siu, O.-L., Spector, P. E., Cooper, C. L., & Lu, C.-Q. (2005). Work stress, self-efficacy, chinese work values, and work well-being in Hong Kong and Beijing. *International Journal of Stress Management, 12*, 274–288. https://doi.org/10.1037/1072-5245.12.3.274

Skinner, E. A. (1996). A guide to constructs of control. *Journal of Personality and Social Psychology, 71*, 549–570. https://doi.org/10.1037/0022-3514.71.3.549

Slez, A. (2019). The difference between instability and uncertainty: Comment on young and holsteen (2017). *Sociological Methods & Research, 48*, 400–430. https://doi.org/10.1177/0049124117729704

Spector, P. E. (1986). Perceived control by employees: A meta-analysis of studies concerning autonomy and participation at work. *Human Relations, 39*, 1005–1016. https://doi.org/10.1177/001872678603901104

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing transparency through a multiverse analysis. *Perspectives on Psychological Science, 11*, 702–712. https://doi.org/10.1177/1745691616658637

Thompson, C. A., & Prottas, D. J. (2006). Relationships among organizational family support, job autonomy, perceived control, and employee well-being. *Journal of Occupational Health Psychology, 11*, 100–118. https://doi.org/10.1037/1076-8998.10.4.100

Thompson, S. C., & Spacapan, S. (1991). Perceptions of control in vulnerable populations. *Journal of Social Issues, 47*, 1–21. https://doi.org/10.1111/j.1540-4560.1991.tb01831.x

Wahl, H. W., & Gerstorf, D. (2018). A conceptual framework for studying COntext dynamics in aging (CODA). *Developmental Review, 50*, 155–176. https://doi.org/10.1016/j.dr.2018.09.003

World Health Organization (WHO). (1990). *Composite international diagnostic interview, version 1.0*. Geneva, Switzerland: World Health Organization.

Wrosch, C., Heckhausen, J., & Lachman, M. E. (2000). Primary and secondary control strategies for managing health and financial stress across adulthood. *Psychology and Aging, 15*, 387–399. https://doi.org/10.1037/0882-7974.15.3.387

Zilioli, S., Imami, L., & Slatcher, R. B. (2017). Socioeconomic status, perceived control, diurnal cortisol, and physical symptoms: A moderated mediation model. *Psychoneuroendocrinology, 75*, 36–43. https://doi.org/10.1016/j.psyneuen.2016.09.025