

Who, and How, Do We Represent? Fifteen Years of Occupational Health Psychology Research  
Reviewed

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data, syntax, full results (including data tables and figures), and supplementary materials are available in an online appendix hosted by the Open Science Framework.

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### Abstract

Psychological research has been criticized for its lack of methodological transparency and representativeness. However, the interrelated nature of reporting and representation issues, and their manifestation in occupational health research specifically, remains undocumented. In this review, we coded sample characteristic- and reporting-related information from all occupational health-relevant studies published between 2010 and 2025 in four leading occupational health journals: the *Journal of Occupational Health Psychology*, *Occupational Health Science*, *Stress & Health*, and *Work & Stress*. We sought to answer two research questions: 1) how representative are samples of global and/or national population characteristics; and 2) how well do researchers adhere to the American Psychological Association's (APA) reporting standards when writing about these samples and their research therewith? Informed by 28 sample- and sampling-relevant APA Journal Article Reporting Standards for quantitative, qualitative, and mixed-methods studies, we coded information from included articles ( $N_{manuscripts} = 1,296$ ;  $N_{studies} = 1,607$ ;  $N_{participants} = 1,630,146$ ) regarding whether certain sample or study attributes (e.g., demographics, contextual setting) and methodological or analytical decisions (e.g., sampling, missing data procedures) were reported, as well as what was reported and in what format. Results empirically document many forms of underreporting (e.g., participant race, socioeconomic status), underrepresentation (e.g., gender minorities, non-Western nations), and overrepresentation or selection bias (i.e., the "privileged worker effect"), as well as areas for standardization, modernization, and clarification to improve occupational health science and its applications. Recommendations for researchers and editors/reviewers, as well as considerations for theory, research, training, measurement, practice, and policy, are presented.

*Keywords:* reporting standards, representativeness, generalizability, sampling, demographics

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**Ethics Approval:** This study involved bibliometric and bibliographic methods and did not involve human subjects (as defined by federal regulations, i.e., 45 CFR 46); as such, it was not subject to or reviewable by DePaul University's Institutional Review Board.

**Clinical trial number:** not applicable.

**Data, Material and Code Availability:** All study data, syntax, full results (including data tables and figures), and supplementary materials are available in an online appendix hosted by the Open Science Framework (<https://osf.io/h8sqe/>).

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It is well-known that samples in psychological research lack diversity, failing to represent broader populations of interest (e.g., Case & Smith, 2000; Henrich et al., 2010a, 2010b; Richmond et al., 2015; Thalmayer et al., 2021). This phenomenon is both common and limiting for the occupational health psychology (OHP) literature: various reviews have documented and lamented this issue (e.g., Bergman & Jean, 2016; Gloss et al., 2017; Michel et al., 2016; Myers, 2016; Rogelberg & Stanton, 2007; Schimmelpfennig et al., 2025; Shen et al., 2011; Spector & Pindek, 2016), summarizing aspects of OHP sampling (in)adequacy. However, repeated calls for “more representative” or “more diverse” samples have largely not been heeded (Allen & French, 2023), despite sizable advancements in other methodological and analytical areas of OHP research (e.g., complex, multi-wave study designs and longitudinal modeling techniques). If we are willing to devote time and attention as a field to these forms of progress, why not do so with sampling as well? There are myriad answers to this question across levels (e.g., limited researcher resources, training, journal priorities). However, comprehensive assessments and solutions are lacking, often overlooking or discounting the pivotal role of manuscript reporting in shaping issues of representation and representativeness.

This review seeks to address these gaps, systematically reviewing OHP sampling and sample-related reporting practices, contrasting findings with established disciplinary standards, and offering a multipronged agenda and associated resources for advancing these key areas of our field’s methodology. In the process, we establish who we (collectively) have represented in fifteen years’ worth of leading OHP research, and the decisions we have made about them: how we have described them, how we have interacted with them, and how we have handled their

data. Spanning all empirical studies published between 2010 and 2025 in four diverse journals heralded by the Society for Occupational Health Psychology (SOHP) as “OHP Journals” (SOHP, 2024), this review provides perspective on issues of sampling practices in the primary research outlets recommended by this leading organization. In doing so, it highlights how and where the prevailing habits that characterize OHP research limit our science and practice, and how and where these practices might be reasonably challenged or offset.

In the following sections, we provide a primer on the interrelated concepts of representation and representativeness, as well as of reporting and transparency, and explore why (under)representation and (under)reporting must be substantively addressed in OHP research—that is, where “business as usual” is simply not good enough. We already know that sampling is not our field’s strong suit, but we have not thoroughly explored the normative reporting mechanisms by which this problem persists nor the specific, sweeping ways it shows up in our research and hampers our field. Through a metascientific lens, we highlight how sampling-related decisions manifest in a leading OHP publications, and generate an actionable, evidence-based agenda for systematic change among trainees and seasoned professionals alike.

### **Representation and Representativeness**

First, we must establish why representation matters, and, relatedly, what it means for a study or sample to be “representative”. Put briefly, our data must come from sources that fit the empirical questions we are asking. There are many ways to judge a sample’s representativeness, and each depends on whether our data align with our question(s) of interest. These questions (and judgments) may be made at different levels and times: by researchers comparing their study’s sample to their objectives at various junctures (e.g., design, collection, analysis, reporting), by readers evaluating the relevance of a set of findings to their own work, or by

reviewers of a literature assessing who has and has not been studied therein. Field-level representation is determined by how individual studies define representativeness, and by extension their selection and implementation of a sampling frame. Put differently, representativeness is an issue of sampling error: unless we are perfectly and completely identifying and studying our population of interest, our work (and field) will always be unrepresentative in one way or another. By the same token, our work will be representative of someone or something, though it may not be who or what we are most interested in. We cannot judge representativeness on a binary scale: instead, it exists along a contextualized continuum.

Sample and sampling decisions must be in alignment with research questions and the populations and/or contexts to which findings are intended to apply and generalize (e.g., Fisher & Sandell, 2015; Grzywacz et al., 2013; Guion, 2002; Landers & Behrend, 2015; Sackett & Larson, 1990). While a variety of non-organizational sampling frames can be valuable for OHP research (e.g., convenience samples, student samples), representation of target populations is especially important for context-centered or context-specific studies, as well as situations in which constructs of interest (and their measurement) or intervention effectiveness are likely to vary across sub-populations (Highhouse & Gillespie, 2009). Moreover, diversity in representation at both the study- and field-level is important, as it enables the investigation of between-group differences in OHP measures, interventions, and theoretical relationships.

**(Under)representation and misestimation in OHP.** Marginalized workers (i.e., less privileged and socially disadvantaged, such as individuals in lower social class positions, racial/ethnic and gender minorities, migrants and immigrants, residents of less developed nations, among others) are known to deal with greater job insecurity and precarity, more mistreatment and harassment, limited access to support, resources, and adequate training, and

threats to health and safety at work (e.g., Benach et al., 2007; Fujishiro et al., 2022; Landsbergis et al., 2014; Leong et al., 2017; Souza et al., 2010). The work and stress research establishing these disparities suggests that underlying stress and coping processes differ as a function of social position, identity, and environment. As such, sampling that ignores privilege in selecting participants, and does not justify such decisions relative to their research aims, may obscure important occupational health mechanisms, differences, and phenomena.

We explore examples of when unrepresentative sampling decisions may have resulted in the misestimation of certain OHP effects or phenomena, specifically in the area of work-nonwork research and practice. We center these examples around the common theme of relative privilege and cumulative (dis)advantage to highlight the features shared by many personal and environmental characteristics, drawing on recent empirical studies and theory development in OHP tying life course perspectives to (occupational) stress and well-being (e.g., Fan et al., 2019; French et al., 2022; Graham & Sinclair, 2024; Granger et al., 2025). Core to these perspectives (e.g., life course stress proliferation, Pearlin et al., 2005; Thoits, 2010) is the idea that life experiences accumulate over time and have downstream effects throughout adulthood. Early challenges and chronic strains, such as poverty, maltreatment, and other adverse experiences, serve as highly influential stressors and stand to propagate more vulnerability to other stressors, strains, and maladaptive stress-related processes later in life. From a sociological life course perspective, these stressors are seen to stem from social structures, including those related to class, age, gender, family roles, and race (among other “systems of stratification”; Pearlin, 1989, p. 242), and are associated with unequal access to and cultivation of resources and a preponderance of potential and realized losses over time. The work-nonwork interface lends itself particularly well to considering these issues, given its focal incorporation of living



situations, family roles, social positions, and culture in research and practice. While we focus on work-nonwork examples, similar limitations, themes, and social position-based theoretical rationale can be applied to other areas of OHP (e.g., safety and health behaviors, workplace mistreatment, aging and retirement; see Frech, 2014; Gonzales et al., 2021; Liu et al., 2024).

***Construct relationships.*** Unrepresentative sampling related to the work context (e.g., occupation, industry, job level, employment status), class (e.g., educational attainment, income), family roles (e.g., relationship and caregiving status, gender, sexual orientation), and culture (e.g., setting, region, country) stands to limit our understanding of various work-nonwork phenomena by mismeasuring and specifying construct relationships. Underrepresenting less privileged individuals in research may result in the misrepresentation of what work-nonwork challenges exist and matter for workers, as well as the ways work-nonwork flexibility (e.g., scheduling, workload, modality, leave) differentially helps or hurts individuals (e.g., Kossek & Lautsch, 2018). Similarly, given the complex relationships between marital status, gender, and financial stability (e.g., Dunga, 2025; Killewald & Gough, 2013), and the earlier-life predictors of adult attachment (e.g., French et al., 2022), oversampling married individuals is likely to overindex better resourced individuals and their stress and work-nonwork processes accordingly.

Parental/caregiver and provider statuses in addition to household structure further contextualize the work-nonwork interface such that experiences for single parents, same-gender parents, and caregivers for individuals at different life stages or with different functional capacities diverge greatly from that of married, heterosexual partners of young children (e.g., Agars & French, 2016; Goldberg et al., 2012; Porterfield, 2002). This makes a workers' access to, need for, and potential or realized benefits of workplace programs more mixed than it might seem when studied with a more heterogenous or "nontraditional" population. Cultural and

contextual factors shape the prevalence, relevance, and importance of certain work-nonwork phenomena as well (e.g., work-family conflict and enrichment; Powell et al., 2009), as do work-nonwork-related ideology, labor practices, and policy (e.g., Poelmans & Sahibzada, 2004).

***Interventions.*** Evidence-based OHP interventions may rely on assumptions about their target audiences that are misguided, too: if a health promotion intervention relies on practicing certain behaviors or skills outside of working hours, the extent to which participants have resources outside of work to accomplish this practice (e.g., neighborhood-, community- and home-based infrastructure and supports to accomplish these behaviors) should be accounted for. Systematic differences in living arrangements and social network size have been documented in different populations (e.g., older lesbian, gay, and bisexual adults; Kim & Fredriksen-Goldsen, 2016) and tied to health outcomes (e.g., Fredriksen-Goldsen et al., 2014), and network size and type affect employment experiences directly as well (e.g., among immigrant populations; Bloch & McKay, 2015; Hagan, 1998). As such, observed successes (or failures) of OHP interventions, and theoretical processes underlying their design and implementation, may be attributable to unmeasured, taken-for-granted factors related to sampling. Our ability to pinpoint study and population sample discrepancies, however, rests upon reporting, which we discuss next.

### **Reporting and Transparency**

Any representativeness assessment or other evaluation of research hinges on what has been reported in a study and in what format. If a study does not report on its participants' gender or does so in a way that does not align with another study (e.g., unclear or nonoverlapping gender categories), this prevents gender-related representativeness assessments or comparisons from being conducted. Similarly, inconsistent reporting poses challenges for evaluating the applicability and generalizability of a piece of research. Readers need access to information

about a study's sampling practices, participants, context, sample-relevant phenomena, and analytical choices (e.g., attrition, data exclusion) to interpret its findings appropriately. With this information, they can understand where and how the study was conducted (i.e., what is being represented), whether these decisions align with the stated study objectives and questions (i.e., whether the data are representative at the study level), and to what extent these decisions generate results that align with or inform their own interests (i.e., whether the data are representative of their target population).

Just as there are many ways to assess representativeness, there are limits to what can reasonably, relevantly, and even safely (e.g., to protect participant confidentiality) be included in a study's data collection and reporting efforts. Still, the current state of reporting and transparency in OHP research still stands to be improved: the OHP literature (as with the organizational sciences more broadly) has been criticized for inconsistent reporting and opaque decision-making, which can limit the interpretability, utility, replicability, credibility, and accessibility of OHP research (Sinclair, 2017; Spector, 2017). Calls for open and integrative science address these issues, encouraging transparency around methodological and analytical practices (Aguinis et al., 2018; Hales et al., 2019). Supporting these calls, journal article reporting standards have been formally (APA, 2018, 2019) and informally published (Eby et al., 2020; Green & Dalal, 2016; Köhler et al., 2017) to promote open and consistent documentation of study procedures, including sample-related characteristics and decision-making.

The American Psychological Association (APA) provides comprehensive Journal Article Reporting Standards (JARS; see Kazak, 2018) spanning quantitative (JARS-Quant), qualitative (JARS-Qual), and mixed-methods (JARS-Mixed) research paradigms as well as guiding discussions of race, ethnicity, and culture in psychological research (JARS-REC). These

standards instruct authors what information they should include in scholarly manuscript sections and provide guidelines for reviewers and editors to judge the thoroughness and clarity of a manuscript's reporting as well as a research project's rigor. Of note for assessing representativeness, the JARS include standards for reporting participant characteristics, sampling procedures, data diagnostics, and even title and abstract framing (i.e., to specify populations studied so they are readily known to readers). There are various JARS supplements for specific research designs as well (e.g., experimental and nonexperimental designs, case or longitudinal studies). Importantly, while the JARS specifies what details to report (e.g., major demographics, participant agreements) and where (e.g., in the methods section), it does not always specify how to report these details or in what format (e.g., average vs. median age, gender categories, what “describing” participant agreements or payments should entail).

Some journals have adopted their versions or elements of such standards (e.g., *The Leadership Quarterly*, 2024), but these standards and recommendations have yet to be systematically endorsed or adopted within OHP. Standardized reporting and transparency not only enable representation and representativeness assessments, but they can help reduce the prevalence of questionable research practices (Banks et al., 2016), close the science-practice gap by making it clearer to which contexts research may or may not generalize (Bartlett & Francis-Smythe, 2016; Rynes, 2012), and inclusively represent the identities and experiences of modern workers (e.g., by standardizing and appropriately using sex and gender terminology, Heidari et al., 2016; Laberge et al., 2020; Tannenbaum et al., 2016). Standardized, transparent reporting facilitates cross-study synthesis, allowing, for example, meta-analysts to test for the effects of substantive and methodological moderators (e.g., Rudolph et al., 2020)—a valuable element of meta-analysis and one that often poses challenges when moderator variables are under- or

inconsistently reported across reviewed studies (cf. Russell & Gilliland, 1995).

Sample- and sampling-related underreporting, and inconsistent reporting, limit OHP science and practice in various ways. Different study designs necessitate different analyses, and they also require different sample considerations and reporting thereof. Forms of convenience sampling (e.g., university- or organization-based, snowball, online panels) hold benefits and limitations depending on what threats to external validity may be reasonably expected, the phenomenon and effect size in question, and what resources researchers have available for specific sample sizes and types. For example, some researchers have contended that certain convenience samples are well suited for elaborate research designs like daily diary studies (e.g., student-recruited samples; Demerouti & Rispens, 2014), while other forms of convenience sampling may conflate important levels of analysis (e.g., between- vs. within-group variance; Newman et al., 2015). Cost-benefit tradeoffs exist for all sampling methods, meaning the selection of a particular sampling approach (and decisions on how to work with participants and their data) must be justified and described. Specific concerns may be especially noteworthy within certain research paradigms or contexts (e.g., generalizability vs. transferability in qualitative research, Carminati, 2018; systematic attrition and missing data in longitudinal research, Goodman & Blum, 1996; outliers, selection, and compensation in online surveys, Arechar et al., 2017; Casey et al., 2017; Landers & Behrend, 2015) and necessitate discussion.

Known issues with certain forms of sampling, such as range restriction and omitted variables in convenience sampling, can be better planned for and mitigated at the study level if the OHP literature consistently provides sampling-related justification and discussion (Johns, 2006; Landers & Behrend, 2015). For example, French and Liu (2024) intentionally limited their sampling of family types to avoid capturing different types of parenting and caregiving norms

(French & Liu, 2024), while Stark and colleagues (2025) prioritized sample heterogeneity to investigate cross-sample consistency of organizational commitment profiles. In light of past research documenting between-province health differences, Hu and colleagues (2023) collected, reported, and controlled for provincial location in China in their study, as well as using propensity score matching to consider whether sample characteristics accounted for observed relationships between job level and well-being (Hu et al., 2023). Newlin (2023) intentionally used “microbatching” in their online study (i.e., making available smaller groups of surveys at different times of day) to minimize systematic sample differences based on task posting time. Each of these efforts was made possible by the extent to which previous studies reported on methodological details related to their sample and sampling decisions. Our review centers on this interrelationship between sampling and reporting.

### **The Present Study**

This review asks questions related to sampling-related practices in OHP research, specifically who we select for these samples and how we represent them and their experiences in our studies. As such, we generate detailed summaries of “average” or normative OHP research participants and study practices which, together, can be used to promote specific, targeted change in how we approach sampling and reporting thereon as a field.

To document these practices, we apply all sample- and sampling-relevant JARS (including quantitative, qualitative, and mixed-methods specifications) to research published in a sample of SOHP-endorsed journals over a period of fifteen years. In doing so, we evaluate a wide array of conceivable avenues for judging a study (and a field’s) representativeness and, relatedly, the transparency and standardization of its reporting. Then, we use our review findings to generate specific recommendations for future sampling and representation decisions and

reporting standardization and transparency. We do not suggest that research published in other outlets or other ways of assessing representativeness omitted from this review are less important or valuable. Instead, we present this review as an initial effort to judge practices in an influential sample of largely U.S.-based, English language journal articles in OHP.

Reviews of sample characteristics or reporting practices have been conducted on a smaller and quite different scale in the past, focusing on specific journals (e.g., Jones et al., 2020; Shen et al., 2011), sample characteristics (e.g., worker status, Michel et al., 2016; sample nationality, Myers, 2016), author and editor characteristics (e.g., race, Roberts et al., 2020), or sample-relevant decision-making (e.g., missing data reporting; Nicholson et al., 2017) or limitations (e.g., Brutus et al., 2010). Moreover, none of these reviews has been explicitly focused on the idea of representativeness, and no published OHP literature (to the best of our knowledge) has explored this idea in breadth and depth nor its relationship to relevant reporting standards. Indeed, limited attention seems to be paid to representativeness and reporting in OHP meta-science and commentary, as well as to related concepts (e.g., sampling error, sampling adequacy; cf. Michel et al., 2016; Sarpy et al., 2012; Walford, 1973).

We systematically investigate two representativeness and reporting research questions (RQs) in this review, using findings from each to construct a plan of action for OHP researchers across sub-disciplines and career stages.

*Research Question 1.* How representative are samples used in modern occupational health psychology research of global and/or national population characteristics and diversity?

*Research Question 2.* To what extent are sample and sampling-related research practices reported in accordance with the APA's reporting standards in modern published

occupational health research?

These research questions, together, give us information about who we have represented, and how, in the past fifteen years of a sizable sample of OHP research. We provide the field's first joint investigation of representation and reporting, grounded in disciplinary guidelines, and build upon our findings to generate a holistic, standardized approach for advancing OHP sample- and sampling-related methodology in the years to come.

## **Method**

### **Transparency and Openness**

Data, R code, study codebook, coding survey, included paper list, study-generated resources (i.e., reporting checklist for authors and reviewers), and complete study results, tables, and figures are provided in an Open Science Framework online appendix (OA):

<https://osf.io/h8sqe/>. This study involved bibliometric and bibliographic methods and did not involve human subjects (as defined by federal regulations, i.e., 45 CFR 46); as such, it was not subject to or reviewable by DePaul University's institutional review board (IRB).

### **Scope and Search Strategy**

The PI collaborated with two graduate research assistants to evaluate and select high-impact OHP journals for inclusion in the project. Various forms of data (i.e., journal impact factors, professional society listings and rankings, journal keywords and aims/scope) were used to rank and assess a list of 35 potential occupational health and organizational science journals. After additional journal inclusion and exclusion criteria were established and applied (i.e., representation on the Society for Occupational Health Psychology's "OHP Journals" list, official journal aims and scope directly mentioning OHP as focus), four journals were selected for review consideration: the *Journal of Occupational Health Psychology*, *Occupational Health*



*Science, Stress & Health*, and *Work & Stress*. Next, using PsycINFO, research assistants conducted an article database search to identify all articles published and indexed between 2010 and 2020 (initial  $N_{articles} = 1,400$ ). 2010 was selected as the earliest year for our review, as it fell two years after the first publication of APA JARS for quantitative research in 2008 and one year after their inclusion in the APA Publication Manual (APA, 2024). Due to the often multi-year nature of the research process from ideation to publication, the search was restricted to begin in 2010, allowing for the potential capture of studies and articles initially designed or submitted for review around the JARS' release but avoiding studies or publications that may well have been completed prior to the availability (and more widespread knowledge) of these standards. Moreover, this timing allowed possible trends in JARS adoption and adherence over time to be considered without holding previously published papers to a contemporary standard. During database construction, the PI developed a systematic coding protocol based on the APA JARS and created a Qualtrics survey therewith (i.e., items corresponding to each of the 28 sample- and sampling-relevant reporting standards and criteria to be coded; see OA Tables 1-3). The database was updated in July 2022 and again in May 2025 to reflect additional published articles from these four journals, resulting in 830 additional articles (total  $N_{articles} = 2,230$ ).

### **Inclusion and Exclusion Criteria**

Primary studies, including papers reporting on studies using archival data, were eligible for inclusion in the present review; more specifically, primary works could include quantitative studies about occupational health topics (e.g., includes health, safety, stress, well-being variables in relation to work, workers, employment, employees, and/or occupations) or qualitative studies pertaining to occupational health topics (e.g., asks qualitative questions that are directly relevant to health, safety, stress, and/or well-being and work/employment). Mixed-methods studies (i.e.,

studies including both quantitative and qualitative components) were included, while case studies, single-subject time-series designs, review papers, meta-analyses, commentaries, and papers based on aggregate data (e.g., labor force participation rate data, worker compensation claims at the county level) were excluded. After applying these criteria to the full article database, 934 (41.88%) articles were excluded while 1,296 (58.12%) articles were included. Specifically, 516 *Journal of Occupational Health Psychology* (JOHP), 184 *Occupational Health Science*, 346 *Stress & Health*, and 250 *Work & Stress* articles were included in the review. Articles were excluded due to not studying occupational health-specific phenomena (67.99%; e.g., studies of children, cancer patients with no reference to employment or work), not reporting on a primary study (31.37%; e.g., reviews, commentaries), or both (0.64%).

### **Training Procedure**

The PI trained six graduate research assistants in coding procedures using a subset of articles until sufficient coding agreement was reached between each coder's responses, the PI's responses, and the original article ( $n = 30$  articles; 2.14% of the initial article database). This training assessed both the accurate application of initial inclusion/exclusion criteria for articles as well as the correct use of the coding protocol for included articles and studies, thus aiming to boost both agreement (i.e., between coders), and reduce the potential for bias (i.e., incorrect application of the protocol or interpretation of the original article). Inter-rater agreement was assessed categorically across all decision points in a coded survey response and was deemed satisfactory at or in excess of 95% (i.e., same survey options selected and values inputted on a cell-by-cell basis). A percent agreement (consensus) approach was taken to assessing inter-rater agreement due to the variable nature of the data being coded (e.g., categorical vs. continuous), the variance in survey questions relevant to an article or study therein (e.g., qualitative study vs.

quantitative longitudinal study), and the multiple rating sources to compare (Stemler & Tsai, 2008). As noted by Villiger and colleagues (2022), inter-rater reliability measures bear limitations. Thus, we follow their recommendation to report the “simplest statistic” in the form of percent agreement as simply an indicator of the rigor of our training (and coding) processes. Following the training period, the PI and research assistants divided the article database and began screening and coding articles, holding weekly meetings to address any disagreements or challenges until resolution and full consensus were established. Disagreements were resolved through discussion, reference to the original article in question, and the coding protocol.

### **Coding Procedure**

Articles deemed relevant for full-text review based on screening were coded independently by one of seven coders in Qualtrics. Information was extracted from each study pertaining to both sample characteristics and sample-relevant reporting practices. At the start of the survey, each coder indicated their identity, the article’s journal of origin, its year of publication, its title, and whether the article’s study/ies met inclusion criteria. If the article was identified as not meeting inclusion criteria, exclusion rationale was provided, and coding was terminated. If the article met inclusion criteria, coders were asked further questions about the study/ies reported therein. For each sociodemographic category that coders identified as reported in a study, further questions specific to this category were then shown and completed (e.g., labels used for race/ethnicity groups, proportions in each group). A full compendium of the survey flow and questions is available in our OA. To review the alignment between survey items, our research questions, and JARS, we direct readers to OA Tables 1 and 2.

As a brief overview, coders answered general study design questions, identified and coded all reported sample characteristics and demographics (e.g., gender, age, socioeconomic

status, education level, relationship status), and provided information about other sample- and sampling-relevant decisions and reporting (e.g., sampling methods used, acknowledgment of ethical considerations, participant compensation, and how outliers and missing data were handled, particularly about issues of systematic attrition or dropout demographic differences; see OA Table 2). This process thus captured both *whether* pertinent items were reported as well as *what* was reported across all articles (i.e., sample- and sampling-relevant characteristics and properties). If an article reported the results of more than one study, coders provided information about each relevant study in separate sections of the survey. For studies that reported on more than one sample, additional coding rules were applied (e.g., coding Time 1 data if multiple time points were available, data from focal employees in the case of dyadic data, data from intervention groups in studies with intervention and control groups). For studies where demographics were reported in distinct sub-groups for a sample otherwise treated collectively (e.g., average age reported for each country within a single sample used for analyses), demographic data were averaged across these sub-groups, with sample size weights applied as available and needed (e.g., in the case of differently sized sub-groups), and coded.

### **Coding Reliability and Quality Assurance**

In addition to meetings and reviewing coder notes, the PI conducted regular coding quality checks to ensure coding protocol adherence, and coders were instructed to “flag” articles that prompted confusion for PI review, discussion, and coding. Consensus was established and disagreements resolved through discussion and reference to original articles.

90% inter-rater agreement was chosen as a cut-off value for these post-training quality checks, as the coding survey was (unintentionally) designed to have different ways to capture the same sort of information, particularly in the study context sections of the survey. In some cases,

for example, a study would reference job levels as occupations or vice versa, and this information could be captured in different items of the same survey completion (e.g., job level or occupation item). As such, coders would capture the correct information in their coding entry but input it into a different area than would be ideal for cross-study comparability. Coders were also encouraged to code quotes from studies as much as possible to facilitate references to the original article. However, slightly different variations on the same quote might have been coded, albeit with the same information (and therefore technically serving as “disagreements”), or quotes might have conflated multiple sources of contextual information better separated for purposes of data analyses (e.g., for a study that described cities and states/regions simultaneously, some coders may have split up the quote while others reported it verbatim).

In each example, according to strictly calculated cell-by-cell consensus assessments, these coding decisions would be deemed “disagreements”, even though they captured the correct information and were cleaned for consistency before analysis. In short, these discrepancies posed no problems for the integrity of the review and were invariably identified and corrected once the full database was compiled. 90%, then, seemed a reasonable cutoff for strictly assessed agreement based on the reporting variety encountered by raters. This level meets or exceeds most established guidelines for favorable levels of agreement-based reliability estimates (e.g., Landis & Koch, 1977; McHugh, 2012). Moreover, if percent agreement had been assessed less stringently (e.g., assessing “effective” agreement, or whether coders captured the same, needed information in the coding procedure), agreement indicators would have been much higher.

Intra-rater agreement (i.e., the extent to which a rater provided the same information about the same studies in separate coding instances; e.g., Belur et al., 2021) was assessed periodically throughout the coding process (i.e., ten times per coder during the initial database

coding process as well as subsequent coding phases after database updating) and held to the training agreement standard (95%). Any discrepancies between coding instances were noted and discussed with the rater to ensure coding approaches did not shift over time (i.e., changes in the application of the coding framework at the within-rater level). No evidence from these assessments, or other coding quality checks, necessitated refresher trainings or coding protocol modifications. As such, while each article in the final dataset was primarily coded by one individual coder, extensive oversight, agreement checking, and data cleaning aimed to mitigate coder “drift” (e.g., Wilson, 2009) and “partially” second-code the database (Villiger et al., 2022). Conservatively, an average minimum of 120 minutes were spent on each article across its original coder, a data cleaner, and the PI who developed the coding protocol.

### **Data Cleaning and Analyses**

Data were cleaned by three graduate research assistants and the PI to ensure alignment of selected options and coded content with each original manuscript and to prepare data for analysis (i.e., removing unnecessary punctuation or text, identifying and replacing missing data, grouping qualitative data and quoted text into new or existing common categories). Analyses were performed in RStudio using the cleaned dataset. Table 1 presents database characteristics.

### **Results**

We now summarize information about the “average” study participant (RQ1) and study (RQ2) considered in our review, respectively, based on the prevailing content reported by and attributes of included studies (see Tables 2 and 3). These provide rough metrics of how and with whom OHP knowledge from the past fifteen years has been generated and reported in four reviewed journals—again, constituting the field’s normative approach to decisions and discussions related to their samples. We provide select representativeness assessments of this

“average” participant as well. Readers interested in a traditional presentation of all study results should consult our OA (e.g., percent of studies reporting each coded characteristic, categories and values reported, detailed representativeness assessments relative to U.S. and global population values). Specifically, we present a full narrative of study results in our OA along with tables detailing and summarizing findings related to each of our coding protocol items. The results narrative presents all review findings in granular detail, while our accompanying tables synthesize these results into more digestible (yet still extensive) formats.

OA Table 4 presents detailed results across all demographic, participant characteristic-related items that were coded, including sample attributes themselves (e.g., mean values, average proportions) as well as how many studies reported these characteristics in certain ways. Similarly, OA Table 5 presents detailed results across all contextual and setting-related items coded, including study attributes (e.g., where or when studies were conducted) as well as how many studies reported these characteristics. Finally, OA Table 6 presents how sample-relevant methodological and analytical information were reported and their proportional incidence across studies. We recommend readers consult these resources to fully understand the data upon which our conclusions, interpretations, and recommendations are based as well as to investigate specific questions or interests in our findings (e.g., if readers are particularly interested in the various ways that participant characteristics like sexual orientation were construed). Thus, if readers have interests in or concerns about specific demographic, contextual, or other sample/sampling-related characteristics or reporting practices as documented by our review, and gaps or limitations associated therewith, we recommend they consult our OA narrative and accompanying tables.

### **The Average OHP Participant**

The average participant in reviewed research is comparatively younger than the

workforce (i.e., 38.45 years old in sample, United States labor force median age in 2023 = 41.6, BLS, 2024a), though it is worth noting that child laborers were not represented in this sample.

Participants are more likely to be cisgender women: women are overrepresented in OHP research (e.g., female gender: comprise an average 57% of reporting samples vs. 47.1% of U.S. labor force) while men were comparatively underrepresented (e.g., male gender: 44% vs. 52.9%; BLS, 2025a). When reported upon, transgender, nonbinary, and gender non-conforming participants were adequately represented (2% compared to 2% or higher globally; Brown, 2022; Ipsos, 2021); however, this reporting was rare (e.g., 1.32% of studies reported proportions of third gender, genderqueer, or non-binary participants).

The average OHP participant is most likely to be non-Hispanic White, with this racial and ethnic group proportionally represented (74% in study vs. 76.3% in U.S. labor force; BLS, 2025a). When other races were reported at all, Black participants were proportionally represented (12% vs. 12%), Asian participants tended to be overrepresented (12% vs. 7.0%), and other races and ethnicities, such as Hispanic/Latinx participants (13% vs. 19.4%; BLS, 2025a) and multiracial participants (7% vs. 10.2%; Jones et al., 2021), were underrepresented compared to U.S. population estimates. Socioeconomic status, unfortunately, was reported in many different formats and currencies and could not be reasonably summarized or compared with population estimates. That said, based on the other characteristics of the reviewed literature (e.g., race, education level, marital status), it is likely that the average OHP participant at the very minimum lives above the poverty line in their nation.

Regarding education, the average OHP participant is college-educated or greater, with highly educated people seemingly overrepresented in research and less educated people underrepresented (see OA; overlapping education categories and ambiguities around degree



status made these comparisons complex). Tenure, both in organizational (8.37 years) and job conceptualizations (9.14 years), appears to be longer than the average U.S. worker (organizational: 3.9 years; BLS, 2024b) but possibly comparable to global workers (tenure construed to entail one's current or main job/profession or employer: 10 or more years; OECD, 2024a). This suggests the average OHP research participant generally experiences a great deal of job security and stability. Accordingly, the normative OHP participant tends to be employed (comprising an average 97% of respective samples when reported) and works 38.58 hours per week, which aligns with U.S. standards (38.3 hours on average; BLS, 2025b) but not global workers (e.g., 1,752 hours working annually, 33.69 hours per week in a 52-week calendar; OECD, 2024b). This person is married, partnered, or cohabiting (comprising an average 65% of reporting samples, compared to 51.14% of the U.S. labor force; BLS, 2025c) and lives in a family or caregiving environment with at least one dependent under 18 (e.g., a child; comprising an average of 46% of reporting samples). U.S. workforce statistics suggest only 30.66% of workers have children (biological, step-, and adopted of the spouse or person maintaining the family; BLS, 2025d) under 18 at home. The average OHP participant is heterosexual or straight (97%), which is higher than global population estimates (80%; Ipsos, 2021).

The average OHP participant speaks English and participates in studies conducted in English or German, with comparative underrepresentation of non-Germanic language backgrounds and study procedures. The citizenship of the average OHP worker is unclear due to underreporting but, as with socioeconomic status, can be inferred to be native-born and a citizen of their country of residence due to other reported characteristics. This leaves immigrants, non-citizens, and foreign-born workers underrepresented in OHP research, though foreign-born workers comprised 19.2% of the U.S. workforce in 2024 (BLS, 2025e), and approximately

3.60% of the global population is estimated to be migrants (IOM, 2022). Furthermore, the largest proportion of research by far is conducted in the United States (36.20%), making the average OHP participant likely to be an American citizen. Indeed, developed, Western countries and advanced economies are overrepresented in OHP research compared to less developed, non-Western, and non-advanced or emerging economies and regions. With respect to the average OHP participant's work context, occupations vary, but this participant works in health services in a white collar, non-supervisory position. Industry and agriculture are underrepresented, as are blue-collar workers (see OA for detailed representativeness assessments of contextual elements).

### **The Average OHP Study**

The average study in reviewed research entails newly collected data across two collections, describing its study population in its abstract (84.90%) but less often in its title (41.30%). Gender (94.52% of studies), employment status (93.34%), and age (92.28%) are regularly reported, while tenure (45.80%), education (40.00%), race and ethnicity (29.99%), language characteristics (22.28%), relationship status (22.34%), and family characteristics and living arrangements (17.67%) are less frequently reported. Finally, socioeconomic status (6.10%), nationality (3.30%), and sexual orientation (1.24%) are rarely reported to describe participants. To describe study context and setting, country (80.46%), occupation (51.21%), and industry (47.91%) are most frequently reported. Study setting (25.58%), data collection dates (23.15%), job type/level (18.42%), and state/region (17.55%) are reported less. Most rarely, study city (5.66%), job context details (3.02%), other community or geographic details (e.g., the urban vs. rural nature of the area; 2.74%), and environmental forces or contextual changes (e.g., viral outbreak; 2.24%) are reported.

In terms of sample-related planning, the average OHP study does not report their target

sample size or how it was determined (5.97% reporting). Inclusion criteria are normally provided (67.64%), with multiple criteria most commonly reported for study or analysis inclusion. These studies rarely test for sample differences based on the application of study inclusion criteria (7.17%), but they tend to observe systematic differences when tested (e.g., excluded participants were younger). In terms of sampling method, the average study reports how they recruit participants (65.11%) but not their sampling approach (26.09%); some studies report no sampling procedure information, however (17.24%). Only 19 studies reporting on their sampling method used purposive sampling (1.43%). Moreover, the average OHP study rarely discusses efforts to sample representatively (9.02%) nor assess the representativeness of this sample relative to their intended sample (9.83%); in short, it does not really describe its intended sample at all. Interestingly, discussions regularly mention strengths or limitations related to the external validity or generalizability of their study (64.34%), but they do not mention the adequacy of their sample size (30.37%) nor the scope of transferability for their qualitative findings (30.34%).

Methods used related to the sample are incompletely described: studies infrequently reference the validity or reliability evidence for their samples (10.81%) or discuss the sample properties from whence that evidence came if referenced (10.18% of studies reporting evidence). Participant incentives are not routinely described (47.67%); when incentives are described, and in monetary terms, participants typically receive \$22.15 without justification of this rate. Other ethical or compliance information is largely not reported, such as IRB approval or adaptations for vulnerable populations (40.51% reporting any such information in the methods section).

Analyses related to outlier testing (3.88%) and missing data considerations (e.g., rates of missingness, empirical evidence regarding the nature of missingness) are infrequently reported (42.56%). When either of these analysis types are reported, they are rarely assessed with respect

to sample-related differences (outliers: 3.33%; missing data: 14.44%). In addition to not describing the study's intended sample, then, little is explored about how the study's actual sample composition is affected by methodological or analytical decisions.

### **Discussion**

Through this review, we make two contributions to the literature. First, we jointly and systematically investigate representation and reporting in OHP research, and do so relative to disciplinary specifications (i.e., JARS). Second, we construct a multilevel agenda and resources for advancing and standardizing OHP sampling practices and transparency. Our review suggests OHP is broadly inattentive to issues of representative sampling and standardized, transparent reporting, relying instead on selective sampling and opaque, inconsistent reporting. Who we choose to represent, and the standard of reporting to which we hold ourselves in discussing them, mutually reinforce one another to sustain issues of underrepresentation and underreporting in the field. Our review sheds new light on this interdependency, the forms it takes in OHP research, and the solutions we can pursue to address it. To this end, we present specific reporting and representativeness recommendations in Table 4, and we offer an agenda for various OHP domains and decision-makers (i.e., researchers, reviewers; theory, research, measurement, training, practice, policy), loosely organized by job analysis task statement elements (i.e., action, object, tool, purpose) in Table 5. This agenda is intended to support the adoption and institutionalization of standard reporting and representativeness improvements, addressing the inconsistencies, gaps, and common practices identified and documented in this review. Each task and implication relate to creating and upholding standards for the conduct and presentation of OHP research, and the agenda highlights mechanisms and roles pivotal to change in this area.

In this review, we identified the person OHP favors and how we describe them (i.e.,

RQ1). Our findings suggest that the OHP literature is unrepresentative, in one way or another, across each of the characteristics considered in this review, and our “average participant” is quite resource-rich. Limited and varied reporting for some characteristics made representativeness assessments complex, yet the general conclusion remains that most OHP research appears to be based on WEIRD (Western, Educated, Industrialized, Rich, & Democratic; Henrich et al., 2010a, 2010b) participants who are relatively young, cisgender, non-Hispanic White, partnered, parenting, and privileged (see Table 2). OHP research suffers from many known issues and selection biases (e.g., the healthy worker effect; Chowdhury et al., 2017). Based on our findings, we suggest that it may also be subject to an even broader *privileged worker effect*, with individuals and organizations who have resources and capital (e.g., economic, social) tending to be recruited, included, and retained in OHP studies more than others.

We also identified how OHP studies tend to sample, interact with, write about, and justify (or fail to justify) our decisions about people and places in research (RQ2). Most studies did not present key demographic and contextual details about their sample and setting, nor did they provide information about their methodological and analytical practices in line with JARS. Some sample attributes were commonly reported (e.g., gender, age, employment status) but divergently and not always inclusively; other attributes were rarely reported (e.g., SES, nationality, sexual orientation). Key information or considerations regarding sampling, materials, procedures, and analyses were omitted from most studies (see Table 3). An impressive paucity of research mentioned purposive sampling methods (or sampling approaches at all), and very few studies assessed their sample’s representativeness relative to their target population nor described taking steps to sample in a representative way. In fact, most studies did not even share their target sample size or population, making correspondence between actual and intended samples difficult

to judge. Specific concerns around missing data, attrition, sampling bias, and outliers were not addressed, despite the fact that the vast majority of sampling was convenience-based in nature. Discussions did, more often than not, mention generalizability limitations, but the omission of other generalizability considerations makes these concessions somewhat dubious.

Importantly for interpreting these findings, in supplementary analyses, we found no evidence of distinctive patterns of difference in representativeness nor reporting over time, nor in relation to other study attributes like journal or study design. These results suggest variability in representativeness and reporting are likely to be better explained by other study-specific factors rather than being products of journal policies, study paradigms, temporal trends, topical or author influence, and study scope. This gives us some amount of confidence in concluding that a) our summaries do not gloss over or obscure systematic differences within our sample of reviewed literature and b) neither the JARS nor calls for sample diversification, unfortunately, have been heeded more as time has passed. Perhaps unsurprisingly, study count did appear to be a limiting factor for reporting (i.e., with multi-study papers reporting less detail) which suggests that the rise in demands for theory-heavy, multi-study papers may come at the expense of sufficient space for methodological detail and sample description. We echo Landers and Behrend's (2015) call for reviewers to avoid asking authors to remove manuscript detail for the purposes of publication space, and we explore additional remedies for space limitations and other issues next.

### **Implications and Future Research**

There are many ethical and practical challenges related to asking about and reporting on participant characteristics. Collecting and reporting more demographic information poses risks to participant confidentiality, increases survey length, and may be challenging to fit within manuscript space constraints. As such, care must be taken to build trust with participants and to

protect participants' data, and researchers should consider context, risk, and purpose when asking individuals to share about their identity. To manage length requirements, alternative reporting approaches (e.g., article appendices or supplements) should be explored. We do not suggest that every possible piece of demographic information be collected, nor that doing so and reporting on it would in-and-of-itself "fix" the issues our review identified; rather, we encourage authors to deeply consider, and discuss their considerations of, what they could collect and report, including exploring alternative reporting approaches or a focus on contextual information when greater disclosure is untenable (e.g., Guzzo et al., 2023).

It is important to remember that representativeness is study- and context-dependent as well. While a literature should seek to be broadly representative, every sample need not be representative of the global workforce, and proactively defining and assessing whether a study's sample is "representative" should be performed in line with the study's aims. Indeed, scholars should ask many questions about representativeness throughout the research process, whether conducting a primary study or secondary review: who do we *want* to represent (i.e., what would align with our research goals and questions)? Who do we *need* to represent (i.e., what gaps or imperatives exist in the literature that might inform our research goals and questions)? Who *can* we represent (i.e., what is feasible, given data collection resources and constraints)? Who *are* we representing (i.e., what sample resulted based on our decisions, at different data collection junctures)? Answers to these questions should then be provided clearly in research reports and manuscripts, no matter the nature of the sample a study uses (e.g., WEIRD vs. representative of another specific population). This practice will clarify when apparent "unrepresentativeness" (e.g., in sample sexual orientation or family attributes, relative to population estimates) was the authors' intention or a study limitation. We do not suggest areas of "overrepresentation"

identified in this review be addressed by sampling those populations less often. Representation is not a zero-sum game. Our goal is to promote deliberation and transparency rather than to increase the representation of some at the expense of representing others.

As discussed earlier, there are cost-benefit tradeoffs for all sampling decisions, and certain samples will be particularly costly to reach with perhaps limited benefits. Studies with more homogenous samples (whether drawn from more historically underrepresented and niche worker groups or more commonly studied populations) allow us to identify and more deeply investigate within-group differences and phenomena, as well as maximize the generalizability of our results to similar situations and groups. More heterogenous samples, conversely, lend themselves to the investigation of between-group differences (e.g., through moderator analyses, multilevel modeling) and broader group- or population-level phenomena, as well as (potential) generalizability and applicability to a broader array of people. These efforts complement one another across a discipline and, when reported upon consistently and transparently, can be readily compared, synthesized, and used to identify future research needs. As such, different approaches to sampling, when implemented with intention, reasonable safeguards, and considerations, all might be useful for different goals and balance costs with benefits well. Still, we highlighted some examples in our introduction of when the “average” OHP study participant is insufficient, particularly when relative privilege and cumulative disadvantage could reasonably shape OHP processes or interventions under consideration.

We recommend readers carefully consider the potential for important theoretical or practical insights when deciding whether a research gap is worth addressing (whether rooted in resource and privilege disparities or another possible boundary condition), and to consider alternative methods or remedies when the costs of representative sampling are not justified.



Incorporating sampling weights into analyses, or adopting a mixture modeling approach (e.g., Asparouhov, 2006), can help account for selection bias and unobserved participant subpopulations, thereby addressing some of the issues with nonrandom sampling (e.g., Andridge, 2023). Also, given the inherently proxy-based nature of identity characteristics in representing life experiences, it may be worth exploring more direct or composite ways of indexing the mechanisms underlying how identity shapes OHP phenomena. For example, we could identify ways to index (dis)advantage that spans groups, sampling for “representativeness” on this metric, treating it continuously, and generalizing to those with adverse as well as privileged life experiences along the continuum (e.g., Xu et al., 2025). We do not suggest that demographic variables or indices be indiscriminately included as control variables in models, however (Breagh, 2008; Spector & Brannick, 2011).

To this point, intersectional concerns are paramount to consider—that is, considerations of how multiple identities and characteristics may interact to produce unique experiences of privilege and disadvantage through societal systems of power and oppression (see Crenshaw, 1991). Of relevance for research and representativeness specifically, intersectional over- and underrepresentation may have various consequences for our knowledge of occupational health phenomena, and apparent representativeness in one area may mask under-representativeness in others (e.g., if Black workers, overall, seem adequately represented in our literature, but not when considering gender, SES diversity, or particular occupational health concerns). Apparent unrepresentativeness may also signal broader issues (e.g., underrepresentation of blue-collar and precarious jobs, which are often held by minoritized individuals or have been offshored from WEIRD countries; Branch & Hanley, 2017; Holland et al., 2021). We must consider how to effectively and ethically access and retain diverse, representative populations in our work to

avoid inattention to segments of society. Particularly when such overlooked populations have been historically marginalized, under-researched, and under-resourced, a reparative and redistributive orientation may be in order (e.g., through intentional oversampling and overrepresentation; Agans et al., 2021). Broader and deeper consideration of the ideas of representation, representativeness, and sampling (error, frames, adequacy, rates) and innovation therewith in the OHP literature is needed (e.g., Kulas et al., 2018). This will help OHP studies with various samples (diverse vs. targeted; commonly studied vs. niche) work together to build an informative and inclusive literature (e.g., through triangulation; Sackett & Larson, 1990).

To document progress in these areas, we need intervention at the journal and publisher level (see also Aguinis et al., 2020; Grand et al., 2017; Schimmelpfennig et al., 2025). If systems could be developed to allow the input or even automatic capture of study meta-data (e.g., regarding sample attributes, study context, methodological and analytical practices, and decision-making rationale), future efforts to document representativeness accurately and comprehensively would be facilitated. These systems can be designed to capture sample overlap with previously studied work (e.g., in the case of studies based on existing data) and provide a holistic picture of sample demographics when authors deem it relevant to present demographics for different subsamples in their article. If systematically implemented, these efforts will be greatly beneficial for meta-analysts and systematic reviewers aiming to consider possible moderators as well.

While these adjustments seem quite feasible, in the interim, adopting and requiring adherence to study reporting standards and providing checklists to this end will also help. All journals have submission requirements, and some provide checklists or links to recommended reporting approaches or guidelines. However, the level of detail provided therein, focus thereof (e.g., on specific demographic categories, data sharing, sample justifications, ethics), and

adherence requirements vary widely. We call for the systematic adoption of JARS as a minimum standard for journal submissions, along with the provision of consolidated, inclusive sample- and sampling-related data collection, and reporting guidelines for prospective authors (e.g., Table 4). In addition to being inclusive, these guidelines should be evidence-based. More research is needed on the best options and collection methods for sample-related information.

As a starting point for some of these efforts, we present the Representativeness and Reporting Roadmap in our OA. This resource includes all sample- and sampling-related information covered in our review and has potential uses for authors and reviewers alike. Authors can use this spreadsheet as a checklist for structuring their manuscript and as a file to submit as supplementary material along with their manuscript. We recommend consulting this spreadsheet when designing data collections to allow for such standardized reporting. Reviewers and editors can use this spreadsheet to evaluate reporting in manuscripts and provide specific recommendations for revisions. Additional extensions are possible, such as the creation of a rubric or evaluation form for manuscript sections pertaining to reporting about samples and sampling-related decisions (e.g., see structured abstract evaluation form in Roux & Burke, 2025). We cite research-based and community-informed “best practices” in generating our recommendations, but these should be piloted and studied in various samples and regularly updated based on feedback and social change.

Demographic trends, technological advancements, and shifting journal policies and reporting standards all stand to complicate as well as potentially help efforts to develop new representation and reporting practices in OHP. With shifting labels for various demographic groups and regions, including different standards and laws instituted in recent governmental actions (e.g., the United States’ exclusive recognition of “two sexes, male and female”; Jaramillo

et al., 2025), collecting participant data in certain ways may be limited or quickly outdated by forces outside of researchers' control. Similarly, as publication requirements and the JARS evolve, and population demography changes, manuscripts may be judged lacking if held to these expectations or societal characteristics. While we advocate for standardization, we do contend that this should be balanced with responsiveness and adaptability at the journal and field levels, as well as acknowledgement of the specific time and place in which research is produced. Relatedly, internet-based data collections present great opportunity for sampling and researching harder-to-reach groups and collecting new forms of data, potentially improving our chances at improving representation in OHP research as well as facilitating more nuanced reporting. However, internet surveys are also subject to data integrity concerns, including non-human "bot" respondents designed to assume certain identity characteristics. As such, the use of these approaches may require extra care, especially when attempting to study vulnerable populations (Bybee et al., 2022; Griffin et al., 2022), and corresponding attention during reporting.

### **Practical Significance**

The findings from our review have a variety of practical implications, whether for interventions and data collection practices in organizations or in facilitating more translatable and accessible science-to-practice communication (see Table 5). Broadly, our review helps identify who, what, and where we need to investigate further, to enable effective occupational health practice in organizations. Our recommendations for both sampling and reporting have a wide array of potential benefits, including helping practitioners identify contextually relevant research and assess generalizability, better tailor interventions to relevant populations and work environments, and ultimately avoid excess resource waste while boosting stakeholder confidence and buy-in. Practitioners should also make note of the predominant privileged worker effect

documented in this review, as OHP research is apparently underrepresentative of marginalized, stigmatized, and/or less-resourced workers. As such, managers and other decision-makers (as well as their workers) from certain industries, areas, and backgrounds appear to be underserved by OHP research (Rynes, 2012). Intervention studies comprised a small portion of the published work reviewed, suggesting more applied research is needed to facilitate the dissemination and implementation of effective practice (Dugan & Punnett, 2019).

Particularly as labor policy shifts (e.g., to reduce protections for gender non-conforming workers, disabled workers, and migrant workers; Katz & Rauvola, 2025), workforce demographics change (e.g., to increase the employment rate of minors; Fletcher & Stephenson, 2025), and practitioners work to adapt, pervasive trends of underrepresentation and deficient reporting and research dissemination in OHP research warrant careful attention. Established construct relationships and interventions may not generalize to workers who do not fit the “average” mold identified in our review; these issues apply to measurement as well, with cultural forces, differential item comprehension or interpretation, and varying content domains and relevance (e.g., French & Agars, 2018) prompting measures applied to individuals from different social positions to potentially function invariantly. Practitioners are well poised to demand better representation (and reporting) from the research community to address these issues.

## **Limitations**

While we strove to overcome past reviews’ limitations and foresee challenges in our project, this review still has limitations of its own that must be considered. First, due to the scope and volume of possible presentations or explorations based on our data, we focused on high-level results comparable to key population characteristics. However, this omitted various intersectional subgroup analyses, as well as a range of population comparisons that would highlight nuanced

areas where research may be more (or less) representative.

Second, we reviewed published research from four journals between 2010 and 2025; as such, our claims regarding representativeness and reporting practices may not apply to published occupational health research in other years or journals. By applying our selection criteria for journals and our own investigative lens and limitations (i.e., U.S.-based researchers whose primary language is English), we limited our sample's cultural and linguistic representation. The lack of consistent publication year correlations or journal differences gives us some confidence that present findings regarding sample attributes and reporting generalize to other similar journals and more recent articles. Still, we do not contend that these journals "should" be representative of global populations, and we are certain there is much valuable OHP research on other populations in other journals. We suggest readers interpret our findings as a reasonable, non-exhaustive summary of practices and populations in the English occupational health literature, based upon a sample of published research that is likely to be cited and applied in the coming decades. As the JARS continue to evolve and expand (e.g., to address race, ethnicity, and culture; APA, 2023), the literature should be assessed against contemporary standards.

Additional limitations concern challenges related to coding. Having one primary coder for each included article disallowed a review-wide assessment of coding agreement; however, we implemented many quality safeguards throughout training, coding, and data cleaning, and all assessments of data accuracy and agreement were favorable and in keeping with literature standards. Moreover, some sample characteristics required assumptions (e.g., gender, when only one group was reported), proved challenging to code (e.g., tenure ranges; characteristics for multiple subgroups or time points, if unclearly described), or could not be viably assessed for representativeness (e.g., SES); if sample characteristics or sampling-related practices were

reported in a location inconsistent with JARS guidelines (e.g., IRB approval in the discussion), they would not necessarily have been captured by our protocol, either. These study limitations also point to limitations of the literature itself, however. We oriented our recommendations to address all we observed—in coded content and limitations thereof—accordingly.

Finally, some studies reported on other study-related characteristics that we did not include in our formal protocol (e.g., shift or contract type, company size, health characteristics). One glaring omission from our protocol was that of disability status. 3.98% of studies reported other study-related characteristics related to health, such as medication use, recreational habits, or diagnoses, but disability was infrequently mentioned and often from a strictly medical perspective (vs. social; Shakespeare, 2006). We recommend occupational health research regularly collect and report on disability status (see Table 4) using questions regarding physical, psychological, and cognitive experiences as in Santuzzi and colleagues (2022).

## **Conclusion**

In this work, we show how (un)representative and (in)consistent decisions regarding OHP sampling and reporting (e.g., who to study, how to categorize and represent identity, who to exclude from analyses) have been over the past fifteen years, and how these issues are intertwined. Then, we use this information to generate an actionable and clear agenda spanning domains and actors for improving research practices in the OHP literature in the years to come. With these evidence-based recommendations in mind, we hope that the OHP literature can move away from the privileged worker effect and toward standardization and modernization, representing and serving the people and interests our field seeks to help. “Business as usual” is not good enough.

Conflict of Interest Statement

On behalf of all authors, the corresponding author states that there is no conflict of interest.



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Table 1. *Study Database Characteristics*

Characteristic	Summary
<b>Study Count</b>	1,607 studies coded from 1,296 articles $M_{studies}$ per article = 1.24 ( $SD = 0.62$ ) 1 study: 1,082/1,296 articles (83.49%) 2 studies: 147/1,296 articles (11.34%) 3 studies: 44/1,296 articles (3.36%) 4 studies: 16/1,296 articles (1.23%) 5 studies: 7/1,296 articles (0.54%)
<b>Web of Science Citation Count</b>	$M_{citations} = 23.64$ ( $SD = 36.06$ , median = 11, range = 0-424)
<b>Sample Size</b>	$M_N = 1014.40$ ( $SD = 7251.7$ , median = 257, mode = 70, range = 4-202,663) Total $N$ across included studies = 1,630,146
<b>Nature of Data</b>	New data collection: 1,289/1,607 studies (80.21%) Data from larger, ongoing, preexisting, and/or previously published project: 318/1,607 studies (19.79%)
<b>Data Collection Type</b>	Single time-point, cross-sectional: 677/1,607 studies (42.13%) Longitudinal (i.e., two or more collections with same sample): 710/1,607 studies (44.18%) Intervention: 56/1,607 studies (3.48%) Experiment: 75/1,607 studies (4.67%) Qualitative: 61/1,607 studies (3.80%) Mixed-methods: 28/1,607 studies (1.74%)
<b>Number of Data Collections</b>	$M_{collections} = 6.87$ ( $SD = 9.44$ , median = 3, mode = 2, range = 1-84)

*Note.*  $n = 1,119$  articles were indexed by Web of Science at the time of coding and are represented in the citation count summary. Total  $N$  across included studies reflects at least some duplicate participants, due to some studies' (whether disclosed or not) reporting on analyses using the same data.  $n = 841$  potentially multi-wave studies (i.e., longitudinal, intervention, experimental collections) are reflected in the number of data collections summary.

Table 2. *Average Participant Characteristics*

<b>Age</b>	38.45 years old
<b>Gender</b>	(Cisgender) woman
<b>Race &amp; Ethnicity</b>	Non-Hispanic White
<b>Socioeconomic Status</b>	Unclear; likely living above poverty line
<b>Education</b>	College-educated or greater
<b>Tenure</b>	8.37 years in organization, 9.14 in job
<b>Employment Status</b>	Employed, working 38.58 hours per week
<b>Relationship Status</b>	Married, partnered, and/or cohabiting
<b>Family Characteristics &amp; Living Arrangements</b>	One or more dependents (e.g., children) under 18 living at home
<b>Sexual Orientation</b>	Heterosexual/straight
<b>Language Proficiency</b>	Speaks English
<b>Nationality, Immigration, &amp; Citizenship</b>	Unknown
<b>Study Country</b>	United States
<b>Occupation</b>	Varies
<b>Industry</b>	Health services
<b>Job Type &amp; Level</b>	White collar, not a supervisor

*Note.* These characteristics are a summary of review findings rather than necessarily being representative of any individual paper's participant characteristics in totality (i.e., as characteristics were reported to varying extents and in varying formats).

Table 3. *Average Study Attributes and Practices*

<b>Design</b>	Two waves of data (longitudinal, intervention, or experimental study)
<b>Sample Size</b>	257 participants
<b>Data Source</b>	New data collection
<b>Title &amp; Abstract Population Reporting</b>	Title does not specify population, abstract describes population
<b>Demographics Reported</b>	Gender (gender binary proportions) Employment Status (proportions, no hours worked) Age (sample average, no range) Tenure (organizational tenure average) Education (proportions of levels/degrees completed) Race & Ethnicity (White proportion) Language Characteristics (language used for study procedures) Relationship Status (proportions) Family Characteristics & Living Arrangements (proportions) Socioeconomic Status (personal or family income) Nationality, Immigration, & Citizenship (proportions) Sexual Orientation (proportions)
<b>Context/Setting Factors Reported</b>	Country Occupation Industry Study Setting Data Collection Dates Job Type and/or Level State/Region City Other Job Context Details Other Community or Geographic Details Environmental Forces or Contextual Changes

<b>Sample Size Planning</b>	Does not report target sample size or how determined
<b>Inclusion Criteria</b>	Reports criteria (multiple) but does not assess for differences between samples or in results based on their application; when assessed, does observe differences
<b>Sampling Procedure</b>	Reports on recruitment method (organizational presentation or distribution) but not sampling approach
<b>Sample Representativeness</b>	Does not discuss efforts to sample representatively or assess representativeness
<b>Prior Psychometric Evidence</b>	Does not provide details about sample from which psychometric evidence was derived
<b>Agreements &amp; Incentives</b>	Does not specify participant agreements or payments, nor provide a specific monetary value when discussing incentives
<b>Ethics &amp; Compliance</b>	Does not provide ethics or compliance information
<b>Outlier Handling</b>	Does not report outlier procedures, nor assess for sample/results differences; when assessed, does observe differences
<b>Missing Data Handling</b>	Does not report missing data considerations, nor assess for sample/results differences; when assessed, does not observe differences
<b>Discussion Limitations</b>	Discusses generalizability, does not discuss sample size adequacy/limitations or scope of transferability

*Note.* “Design” specifies modal number of data collections. “Sample Size” is median reported *N*. “Demographics Reported” and “Context/Setting Factors Reported” are presented in order of reporting rate (most reported across studies to least reported). Parentheses provide a characterization of the most common reporting type, format, or approach, as relevant.

Table 4. *Recommendations for Representativeness and Reporting*

<b>Attribute</b>	<b>Representativeness Recommendations</b>	<b>Reporting Recommendations</b>
<b>Age</b>	Greater age diversity needed, including more relatively middle-aged and older workers	Report age as an overall sample average along with observed range
<b>Gender</b>	Greater gender balance needed, including representation of individuals outside gender binary	Collect and report on gender using inclusive options (e.g., APA, 2016; NASEM, 2022)
		Use the terms “gender” and “sex” appropriately and not interchangeably (e.g., APA, 2022a)
		Do not only report one gender category (e.g., % women)
<b>Race &amp; Ethnicity</b>	Greater racial & ethnic diversity needed, including multiracial participants and non-U.S. race/ethnicities	Collect and report on race using inclusive options (e.g., APA, 2022b; APA, 2023; Flanagin et al., 2021)
		Avoid outdated terminology (e.g., “Caucasian”) or referring to people of color as a broad “minority” or “other” group
		Do not only report one race category (e.g., % White)
<b>Socioeconomic Status</b>	Unclear, but considering other reported attributes, would recommend greater SES diversity, including those with lower SES	Collect and report on objective and subjective proxy SES indicators (e.g., average annual income, subjective social status; see APA, 2015) in addition to a composite (e.g., NCES, 2012)
<b>Education</b>	Greater educational attainment diversity, including individuals who have not completed high school or college	Collect and report data in established education categories (e.g., national census standards), along with specifying in-progress vs. attained degree status
		Reporting the sample average years of education completed would facilitate cross-country comparison
<b>Tenure</b>	Need more participants with shorter tenure (job and organizational)	Collect and report both job and organizational tenure (clearly specifying the type) as an overall sample average
<b>Employment Status</b>	Greater employment diversity, including part-time workers and other worker statuses	Specify worker time status (i.e., full- vs. part-time) and report on other statuses as appropriate (e.g., sick leave, unemployment)
		Collect and report on average weekly hours worked



Attribute	Representativeness Recommendations	Reporting Recommendations
<b>Relationship Status</b>	Greater relationship status diversity, including representation of unmarried workers and nontraditional structures (e.g., non-monogamous relationships)	Report on relationship status in standard, expansive categories unless legal status is of interest (e.g., “partnered” vs. “married”)  Report separately from living arrangements and parenting status if possible
<b>Family Characteristics &amp; Living Arrangements</b>	Greater family status and living arrangement diversity, including individuals with adult caregiving responsibilities, living alone, and without or apart from children	Collect and report number and age of dependents, caregiving hours and status (e.g., shared vs. sole), and household size (e.g., as averages)
<b>Sexual Orientation</b>	More balanced representation of both heterosexual and LGB workers	Report on sexual orientation using inclusive options (e.g., APA, 2022c, NASEM, 2022; SMART, 2009)  Consider whether identity, behavior, and/or attraction are of interest and assess accordingly  Report at the appropriate level (i.e., to characterize an individual’s orientation vs. the nature of their relationship)
<b>Disability Status</b>	-	Collect and report on disability status related to physical, cognitive, and psychological disability, impairment, and health issues (Santuzzi et al., 2022)
<b>Language Characteristics</b>	More non-English-speaking or non-Germanic language populations (and study procedures)	Report on sample language proficiency (e.g., as study requirement, as participant characteristic) as well as language used for study procedures and materials
<b>Nationality, Immigration, &amp; Citizenship</b>	More (im)migrants, non-citizens, foreign-born workers, and other resident statuses, especially considering global migration patterns and displacements	Collect and report on nationality, (im)migration status, and citizenship with care (e.g., in light of legal concerns) and clearly distinguish if reporting  Avoid characterizing non-citizens, immigrants, or different nationalities as “other,” unless for safety reasons
<b>Geographic Context &amp; Setting</b>	More studies conducted in non-Western and less developed nations, as well as non-advanced/emerging economies (i.e., less WEIRD-centrism)	Provide geographic details with discretion, reporting at minimum on study country followed by other levels as appropriate  Describe setting and contextual attributes, including data collection dates (i.e., as study may be published long thereafter) and relevant contextual changes or environmental/cultural forces

Attribute	Representativeness Recommendations	Reporting Recommendations
<b>Work Context &amp; Setting</b>	More studies conducted in non-service industries and with blue-collar workers	Report sample occupation and industry details in line with federal (e.g., SOC titles, NAICS codes) or preferably international (e.g., ISCO, ISCI) classification systems
		Report on both sample collar type (e.g., blue, white, pink) and job level/supervisory status
		Specify how sample size was selected (e.g., based on <i>a priori</i> power analysis) and what target was
<b>Sampling &amp; Sample Criteria</b>	Leverage available methods and tools to recruit and retain representative samples, assess extent to which approaches were successful, and provide specific (representativeness) recommendations for future research and application	Report inclusion and exclusion criteria and assess for differences (between samples, in results) based on their application
		Specify recruitment (e.g., online panel) and sampling (e.g., stratified) methods, undertaking representative approaches that align with study goals
		Assess sample representativeness with appropriate comparison groups
<b>Prior Psychometric Evidence</b>	Consider whether selected measurement tools are likely to retain psychometric integrity and attributes (e.g., validity, reliability) in study sample, and represent constructs and experiences as intended	Explore strengths and limitations of sample size and study/context (i.e., in relation to generalizing or transferring findings) in discussion
		Provide evidence that measurement tools are appropriate to use with/relevant to study sample (e.g., prior validation, pilot data, content analysis)
<b>Participant Agreements &amp; Ethics</b>	Consider how incentives, agreements, treatment of, and protections for participants may affect sample representativeness (e.g., differentially incentivizing or accommodating participation)	If reporting coefficients from past studies, provide details about sample(s)
		Report clearly and specifically on agreements made with participants, including an evaluation of fairness/justice
<b>Outliers &amp; Missing Data</b>	Consider the extent to which data analysis decisions affect (e.g., reduce) sample representativeness and why outlying and missing data patterns may emerge in relation to sample characteristics (e.g., reasons for differential attrition, extreme responding)	Confirm necessary ethical board approvals (e.g., IRB) and protections relevant to study design and population
		Plan and implement outlier and missing data procedures
<b>Outliers &amp; Missing Data</b>	Consider the extent to which data analysis decisions affect (e.g., reduce) sample representativeness and why outlying and missing data patterns may emerge in relation to sample characteristics (e.g., reasons for differential attrition, extreme responding)	Test for and report on differences between samples, patterns of missingness or outliers, and in results with respect to outlier and missing data cases

Note. “TGNC” = transgender and gender-nonconforming. “LGB” = lesbian, gay, and bisexual.

Table 5. *A Proposed Agenda for Occupational Health Science Domains and Stakeholders*

	<b>Reviewers &amp; Editors</b>	<b>Authors &amp; Investigators</b>	<b>Theory, Research, &amp; Measurement</b>	<b>Training</b>	<b>Practice</b>	<b>Policy</b>
<b>Action</b>	Evaluate with reporting standards & representativeness concerns in mind, asking for sample and sampling justification, details, and analyses	Account for sample- and sampling-related reporting standards & representativeness issues across all stages of the research process (study design, data collection, analysis, writing)	(Re)consider the extent to which existing theory has been tested and revised, research designed and conducted, and scales validated with and for certain types of workers	Educate on reporting & representativeness issues and best practices early and often, encouraging their application in projects, class discussions, etc.	Design and interpret with reporting & representativeness in mind	Advocate for systematic adoption of inclusive and representative data collection practices & reporting standards
<b>Object</b>	Unpublished peer-reviewed research publications	Empirical studies	Published literature	Students and trainees	Organizational data	Research instruments & norms (e.g., at federal level)
<b>Tool</b>	Review findings (e.g., see Tables 1-6) & APA JARS					
<b>Purpose</b>						
<b>Accessibility</b>	To increase comprehensibility and predictability for journal readers from varying backgrounds	To have relevant and interpretable data available for various research audiences	To prompt the development and use of more widely applicable and relatable theory, research, and measurement tools	To make knowledge available during career stages, when such ideas may be easier to learn and practice	To have relevant and interpretable data available for organizational members	To improve the legibility and relevance of summary data for citizens and decision-makers across cultures, and to make data collection experiences more predictable and convenient for participants

	<b>Reviewers &amp; Editors</b>	<b>Authors &amp; Investigators</b>	<b>Theory, Research, &amp; Measurement</b>	<b>Training</b>	<b>Practice</b>	<b>Policy</b>
<b>Inclusion</b>	To diversify scholarship, perspectives, and conclusions in journals and the field	To involve people and places of interest, especially those historically underrepresented, in the research process	To expand whose experiences and voices are represented in our knowledge base	To engage new and diverse generations of scientist-practitioners in improving research practices	To sample and capture worker data with more nuance and intention	To maximize accurate and compassionate representation of sample attributes and identity
<b>Synthesis</b>	To ground evaluations of study novelty, rigor, and potential impact (among other criteria) in a shared framework	To permit more comprehensive and fine-grained meta-science (e.g., meta-analysis, systematic reviews)	To identify areas of deficiency as well as strength in the literature, as guides for future endeavors	To integrate various aspects of methodological and statistical education toward a common purpose	To enable better over-time, within-organization data comparisons as well as with published research and data	To facilitate the comparability and portability of aggregate data across groups and contexts
<b>Credibility</b>	To address concerns in and outside of the academy about replicability, generalizability, and selective reporting	To strengthen methodological and analytical rigor, ethics, and other issues of interest to publication outlets, funding bodies, and consumers	To confront systematic biases in the literature that undercut trust in science and researchers	To align course content and professional development with modern concerns such as transparency and representation	To gain influence with organizational stakeholders—both those making decisions and those being assessed	To boost confidence in research processes and procedures, and thereby collected data and their interpretation
<b>Utility</b>	To augment the reach and potential uptake of published knowledge, and public interest therein	To generate research with a higher likelihood of and fewer barriers to translation into communities	To illuminate (at least some of) the factors sustaining the science-practice gap	To provide transferrable skills and knowledge that span career paths	To improve implementation outcomes and intervention success	To maximize the applicability of data and insights therefrom across contexts