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WEIRD and Beyond: Sample Diversity and Reporting Practices in Empirical Human Resource Development Research

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WEIRD and Beyond: Sample Diversity and Reporting Practices in Empirical Human Resource Development Research

Abstract

Building on concerns about the overreliance on Western, educated, industrialized, rich, and democratic (WEIRD) populations in social science research, this study examines who empirical human resource development (HRD) studies published in journals of the Academy of Human Resource Development (AHRD) investigate and how research samples and their contexts are reported, using a 2016–2025 census of 326 empirical articles (338 sample units) in *Human Resource Development Quarterly* and *Human Resource Development International*, the two AHRD-affiliated journals that carry empirical research. Using a framework that spans individual, organizational, and sociogeographical contexts, the analysis revealed persistent concentration in particular research populations within this AHRD-affiliated corpus. Managerial perspective samples (68.0%) dominated, white-collar samples (75.4%) far outnumbered blue-collar samples (1.8%), disabilities (0.9%) and sexual orientation (1.5%) were rarely reported, and large-scale organizations (48.2%) outnumbered small and medium-sized enterprises (8.3%). Studies drawing on WEIRD-country data (55.0%) and single-country designs (82.8%) dominated, and cultural context was often merely identified by geographic location (31.7%) rather than linked to findings. A latent class analysis identifies four bias configurations, led by a Western Managerial class (54.1%) and a Non-Western Large Corporate-Managerial class (15.4%), revealing considerable large-firm and managerial concentration even in non-Western studies. Although sampling methods were reported in 95.0% of studies, convenience and purposive sampling accounted for 73.4%, and 87.6% of all analyzed sample units omitted two or more key contextual variables. These findings suggest that concerns about research sample diversity extend beyond the WEIRD distinction to occupational and organizational contexts, while limited contextual reporting further constrains the interpretation and transferability of findings. By examining both sample diversity and reporting practices, this study highlights broader challenges for developing inclusive and contextually grounded knowledge in HRD and other applied social sciences.

Keywords: sample bias, sample diversity, WEIRD, empirical human resource development research, latent class analysis

Empirical claims in the social sciences are only as general as the people from whom the evidence is drawn. Henrich et al. (2010) made this point sharply by showing that findings presented as universal human psychology rest disproportionately on participants from Western, educated, industrialized, rich, and democratic (WEIRD) societies, which account for only about 12% of the world's population. The concern has since traveled beyond psychology. Schimmelpfennig et al. (2025) documented a lack of sample diversity in organizational research and extended the critique to the organizational level, including the underrepresentation of employees at small and medium-sized enterprises (SMEs). The consequences of such narrowness are not the same across fields. In basic research, a skewed sample limits what can be claimed; in applied fields, whose findings are translated into interventions for particular workplaces, it also shapes what is done, and to whom (Calder et al. 1981; Rousseau 2006).

Human resource development (HRD), the applied field concerned with the development of people at work, is a particularly revealing case for three reasons. First, HRD is defined by its attention to people situated within the context of work and workplace organizations (Ruona 2000), so its research subjects are not incidental to its knowledge claims but constitute its object. Second, the groups that HRD scholarship itself has warned are at risk of being overlooked—low-wage and nonmanagerial workers, employees of smaller organizations, and workers whose voices are marginalized by privileged professional samples—are precisely the people whom HRD practice is meant to serve (Nolan and Garavan 2016; Scully-Russ 2005; Shuck et al. 2016). Third, the field has repeatedly professed sensitivity to context and to the limits of theory built in Western corporate settings (Anderson et al. 2024; Wang and Doty 2022). Whether its evidence base lives up to these commitments has not been examined systematically. Critiques to date have focused on particular excluded groups, such as workers with disabilities (Procknow and Rocco 2016) or transgender workers (Collins et al. 2015), and assessments of organizational research as a whole leave open how sampling plays out within a field that has its own research subjects, applied commitments, and reporting conventions. This problem of research subject bias converges on two broad axes. The first concerns the actual state of bias by level of context: who is studied, and within what context? The second concerns how researchers treat those subjects in terms of linguistic expression, sampling, and reporting practices, including whether terms such as "organization" or "employee" are used without specifying what or who they actually denote.

These concerns draw particular attention to *Human Resource Development Quarterly* (HRDQ) and *Human Resource Development International* (HRDI) among the four journals published under the aegis of the Academy of Human Resource Development (AHRD). *Advances in Developing Human Resources* (ADHR) publishes special issues organized around specific themes, whereas *Human Resource Development Review* (HRDR) specializes in literature reviews and theory-building articles. HRDQ and HRDI, by contrast, regularly carry original empirical research, and HRDI places particular emphasis on international and multicultural perspectives. Although affiliation with AHRD does not, in itself, guarantee a universal HRD research standard, AHRD-affiliated journals function as a platform to which researchers from a comparatively wide range of countries and institutions submit and publish their work. In comparison to single-country HRD journals such as those in Korea, the United States, the United Kingdom, China, Thailand, and Japan, articles published in HRDQ and HRDI are therefore an appropriate research resource for examining the specific patterns of research subject bias that motivate this study. Considering the rise of the WEIRD concept (Henrich et al. 2010) and recent precedents in HRD literature reviews (e.g., Fordjour et al. 2025; Thomas et al. 2022), we set the past decade (2016–2025) as the analytic period.

“Empirical HRD research” in this study denotes the empirical articles published in HRDQ and HRDI, not the entirety of empirical HRD research worldwide; studies in other international and country-specific HRD journals lie outside the analytic scope (see Limitations). Our claims are therefore claims about the empirical research that AHRD-affiliated journals make visible.

Given this scope, this study adopts an integrative analytic framework that moves beyond single-dimensional categorical analyses of research subjects. Individuals are simultaneously embedded in geographic, organizational, and personal contexts (Tsui et al. 2007), and the influence of personal and

contextual systems on individual growth and development—matters of considerable importance in HRD—has been articulated through Bronfenbrenner's (1979) ecological systems theory, which HRD research has applied as an ecosystem perspective linking individual and environmental levels of analysis (e.g., Younis et al. 2024).

The second axis—how researchers treat those research subjects—moves one step beyond the samples themselves to the researcher as the agent who produces the text. How researchers treat their subjects is grounded in the situated microprocesses of language (Locke and Golden-Biddle 1997) through which they construct the manuscript text, so we also attend to how research subjects are rendered in empirical HRD articles.

A representative issue is whether the terms HRD researchers use to refer to research subjects or contexts—such as "organization," "employee," or "leader"—are decontextualized. When used without regard for their actual referent, such terms tend to imply little more than a vague call to strengthen an organization's "institutional" support; a term treated like a master key that can signify almost anything may explain nothing at all in the end (Alvesson and Blom 2022). Another issue concerns how research subjects are constituted at the aggregate level—that is, sampling. Although sampling may appear to be a narrow methodological issue, as a visible mode of research practice it is a channel through which researchers reveal their basic assumptions about a phenomenon and human existence, and it functions as a gateway to analyzing, predicting, interpreting, and understanding phenomena of interest to HRD. This study is therefore intended to diagnose how research subject bias is related to an absence—or vacuum—of context through the sampling practices employed in AHRD-affiliated empirical research.

Moreover, existing research subject reviews as part of broader research trends have largely been limited to independently describing single-dimensional categories—such as distributions by country, industry, or organizational size—making it difficult to examine research subject bias in a multidimensional manner that considers the overlap of individual, organizational, and geographic contexts. Beyond the HRD case, the contribution is also methodological and portable. The levels-of-context framework, which links the individual, organizational, and sociogeographical characteristics of research subjects to how those subjects are described, and the latent class approach to identifying configurations of bias do not rest on HRD-specific constructs. They can therefore be adapted to other applied fields whose findings are translated into interventions for particular workplaces or populations, such as education, public administration, or healthcare management. We thus offer this study both as a diagnosis of one field and as a template for examining whose evidence underlies applied social science.

Accordingly, this study analyzes research subject bias and deficits in reported information in the empirical HRD articles published in *HRDQ* and *HRDI* over the past decade, exploring the lack of diversity and the potential decontextualization across this body of research. This purpose is specified through two research questions—(a) who is studied, and within what context, in empirical HRD research published in AHRD journals? and (b) how have researchers treated those research subjects?

Literature Review

Representativeness, context, and the research subject

A critical examination of research subjects first concerns their representativeness. Attending to whether the people studied mirror the population to which findings are meant to apply is directly intended to support the generalizability of research findings (Calder et al. 1981; Sears 1986; Swanson 2005). Representative Bureaucracy Theory in public administration (Selden 2015), for example, attends to the extent to which the composition of a bureaucratic body—by race, gender, and so forth—mirrors that of the population it serves (e.g., the proportion of Black police officers). The analytic findings of this study should accordingly be interpreted with reference to representativeness and generalizability criteria.

Representativeness alone, however, does not secure generalization, which remains elusive without a sufficient understanding of context. Johns' (2006) distinction between omnibus context—encompassing who, where, when, and why—and discrete context, composed of task and social characteristics, enables a more concrete assessment of the degree to which context has been adequately understood. Concrete factors that may be considered in such an assessment were detailed in the Participant Characteristics reporting module of Appelbaum et al.'s (2018) Journal Article Reporting Standards (JARS)–Quant, which specifies demographic characteristics (e.g., age, gender, race/ethnicity, education, employment status); the population; sampling procedure, and sampling frame; and participating organizations' type, size, and institutional context. What must be guarded against is insufficient information about the research subject that borders on decontextualization and the exclusion and erasure that result from concentrating on particular research subjects.

Regarding leadership—a topic of sustained interest in HRD research and practice—it is difficult to deny that the theories underpinning leadership research have largely been established within the corporate contexts of Western societies (Lonati and Van Vugt 2024). Research on change management and innovation also warrants reconsideration: because SMEs tend to be subsumed under the generic category of "organization" (Nolan and Garavan 2016), it remains unclear whether these settings have been studied sufficiently in their own right. Even in corporate governance research, evidence has relied predominantly on samples of large corporations, although these constitute only a very small percentage of all business enterprises (van Essen et al. 2015). Therefore, the question of who is studied and the underlying issue of research subject bias is not confined to the individual level but must also be considered at the organizational level, where people form associations, and can also be examined across higher-order social systems such as countries and other regions.

This approach makes it possible to address the insufficiency of research subjects' information alongside levels of context. If, following a careful, line-by-line reading of an article, it is difficult to specify who the study is about or identify to whom its findings might first be applied, this may indicate both research subject bias and an information deficit concerning the research subject—one inevitably linked to an absence of context and, ultimately, decontextualization. This concern also touches the deeper issue of underlying universality. The critique that HRD theory produced in the West—Europe and North America—represents the experience of less than 25% of the world's population has led to proposals of an alternative concept of Cultural HRD (Anderson et al. 2024), and mainstream HRD theory has been shown

to rely on assumptions and concepts derived from open, Western contexts (Wang and Doty 2022). Similar to the critique that the "organization" category has been theorized almost exclusively within the context of large corporations, neglecting SMEs' informality (Nolan and Garavan 2016), the risk of decontextualization can be said to lie in the pendulum swing between universality and locality.

Representativeness and context are thus two distinct but complementary conditions for the usability of empirical evidence. Representativeness concerns whether the people and settings studied cover the range of circumstances to which findings are meant to generalize; context concerns whether readers receive enough information about those people and settings to judge where findings may transfer (Johns 2006; Rousseau 2006). A body of research can fall short on either condition: evidence may be concentrated in a narrow range of samples, or samples may be described too thinly for their boundaries to be judged. The two research questions of this study correspond to these two conditions.

HRD research subject bias

We next examine previous research to identify the forms of exclusion and gaps that have actually accumulated within the HRD literature. The starting point of this study was problematizing research subject bias—a concern, much like the WEIRD rhetoric, with empirical findings concentrated on a particular category of people and the consequent erosion of generalizability and applicability. However, research subject bias is not static but introduces additional concerns of exclusion (gaps) and the erasure of voices. These terms are not treated as conceptually distinct or as forming a sequential causal relationship; instead, they function as a rhetorical device for capturing, from multiple angles, how research subject bias has been treated in HRD research and what issues it raises.

Representative examples include a research bias favoring able-bodied individuals that excludes perspectives from people with disabilities (Procknow and Rocco 2016) and the issue of low-wage workers' path dependency (Scully-Russ 2005), both raised within the HRD scholarly community. Someone like the woman next door who works part-time as a cashier at a large discount store or a cousin who works on the shop floor while living with autism is rarely encountered in HRD research. This raises the question of whether HRD research and researchers prefer fabricated figures that can be captured in a single shot within a research article, rather than the people we might actually meet and converse with.

Bias toward a particular category of people ultimately gives rise to the problem of exclusion (gaps), suggesting that social exclusion is reproduced not only in the lifeworld but also in the scholarly world. This pattern is concurrent with the privileging of white-collar and professional workers observed in employee engagement research (Shuck et al. 2016). Further reference points include a paucity of research on nonregular workers in career development research (McDonald and Hite 2005), the erasure of minority and marginalized groups' voices across HRD research more broadly (Bierema 2009), and leadership research applying intersectionality, which captures the compounded manifestation of exclusion and erasure (Sim and Bierema 2025).

Our research concern, however, is not confined to the "unevenness" of research subjects' surface-level composition; it extends to the underlying process of knowledge generation. Neither the broad problematizations of research subjects that have received comparatively little attention in existing HRD

research (Bierema 2009; Sparkman 2019) nor the series of attempts to identify research gaps for specific minority groups (Collins et al. 2015; Procknow and Rocco 2016; Torraco 2016) have systematically and empirically analyzed who was actually sampled as a research subject in empirical HRD research. This is precisely where the present study's contribution lies.

Levels of context: An analytic framework

To determine who has been excluded in empirical HRD research—thereby producing research gaps and potentially erasing their voices—our aim requires an analytic framework capable of capturing this state of affairs. To do so, we assign levels to the contexts surrounding people as research subjects. This framework, which we call levels of context, references Schimmelpfennig et al. (2025) and is specified according to individual, organizational, and social levels. Gender, age, employment, position, and department, along with disability status and sexual orientation, correspond to individual-level context, whereas organizational size, type, industry, and governance structure comprise the organization-level context. Social factors that operate at country or regional levels—such as culture, politics, history, and religion—correspond to geographic context. We operationalized this dimension around the descriptions that are observable in the article text at country and cultural levels—covering the country of data collection, continent, whether the design was single- or multi-country, and whether cultural context was described in relation to the study's findings. Analysis by levels of context can reveal not only the state of single dimensions, such as organization size, but also bias in research subjects in a more multidimensional way.

As levels of context address the question of who is studied and within what context, a further concern of how researchers actually construct that subject must also be examined, and sampling is its most visible expression. If convenience sampling accounts for a substantial proportion of the methods used to determine research subjects' size and scope—in a sense distinct from the global-representativeness issue raised in prior research (Henrich et al. 2010)—this may indicate that empirical HRD research is being conducted with a WEIRD sample composition. The prevalence of convenience sampling was previously documented in *HRDQ* articles more than two decades ago (Dooley and Lindner 2003).

Method

Target journals and data retrieval

To critically examine research subject selection and reporting practices within the HRD field, this study targets empirical articles published in *HRDQ* and *HRDI* over a 10-year period spanning 2016–2025. *HRDQ* and *HRDI* are premier empirical and theoretical knowledge dissemination channels officially sponsored by the AHRD and the University Forum for HRD (UFHRD), covering North American and European/international academic spheres. Of the four AHRD-affiliated journals, only these two were targeted because HRDR and ADHR primarily publish literature reviews, theory-building articles, and thematically organized special issues rather than a regular stream of original empirical studies.

We collected bibliographic records from the Web of Science and identified and retrieved articles from respective publishers' official archives (Wiley Online Library for *HRDQ* and Taylor & Francis Online for *HRDI*) on April 1 and 2, 2026. Because all articles published in the 2016–2025 period were reviewed and

downloaded, we did not employ a keyword-based search strategy. The 10-year period followed the growing prominence of Henrich et al.'s (2010) concept of WEIRD populations and the accumulation of critical discussions concerning sample bias, participant diversity, and research decontextualization.

Inclusion and exclusion criteria

To ensure methodological transparency and replicability, as emphasized in Torraco's (2016) methodological guidelines for integrative literature reviews, explicit inclusion and exclusion criteria were established and consistently applied. Studies were included if they (1) were full-length research articles published in *HRDQ* or *HRDI* between 2016 and 2025 and (2) empirically analyzed data on actual workplace members such as employees and managers or organizations. Eligible data included surveys, interviews, observations, and experimental data collected directly by the researchers, as well as publicly available microdata from large-scale workforce panel surveys administered by national governments or public institutions. Based on these criteria, nonempirical research publications such as editorials and corrigenda were excluded in the first stage. Conceptual and theoretical articles, literature and scoping reviews, meta-analyses, bibliometric studies that treated published scholarly texts as the units of analysis, and other secondary or nonempirical studies that lacked empirical data on human participants or organizations in workplace settings were subsequently excluded.

Following 2020 Preferred Reporting Items for Systematic reviews and Meta-Analyses guidelines, the screening process proceeded through three stages—initial identification (N = 659), title and abstract screening (excluding 98 nonresearch documents), and full-text eligibility appraisal (excluding 235 conceptual, review, and meta-analytic papers), yielding 326 empirical articles. Because several studies adopted multi-sample designs (e.g., Study 1 and Study 2 addressing distinct organizational populations), these articles yielded 338 distinct empirical sample units (160 from *HRDQ* and 178 from *HRDI*) as the final unit of analysis (Table 1).

Table 1

Article Selection and Units of Analysis

Stage	Target/Document Source	Frequency (N)	Exclusion Criteria and Rationale
1. Identification	Articles published in *HRDQ* and *HRDI* (2016–2025)	Total N = 659 (*HRDQ*: 251/*HRDI*: 408)	Complete bibliographic extraction from official publisher databases
2. Screening	General research articles	Total N = 561 (*HRDQ*: 203/*HRDI*: 358)	Nonresearch documents excluded: n = 98 (Editorials: 92 [*HRDQ*: 44, *HRDI*: 48]; Errata: 6 [*HRDQ*: 4, *HRDI*: 2])
3. Eligibility	Empirical research articles	Total N = 326 (*HRDQ*: 151/*HRDI*: 175)	Nonempirical & secondary literature excluded: n = 235 (Conceptual: 146; Reviews: 52; Forums: 19; Methods/Simulations: 12; Meta-analyses: 6)
4. Included Sample	Final independent empirical sample units	Samples: N = 338 (*HRDQ*: 160/*HRDI*: 178)	The 315 single-sample articles contributed 315 analytical units, while the 11 multi-sample articles contributed 23 analytical units

Note. HRDI = Human Resource Development International; HRDQ = Human Resource Development Quarterly.

Analytical framework and coding architecture

During data extraction, basic bibliographic information (article ID, title, authors, institutional affiliations, and countries) and methodological characteristics (research approach, cross-sectional or longitudinal design, use of multilevel data, analytical methods, and analytical software) were coded. To systematically examine the contexts of the populations studied, we developed an analytical framework by adapting the "levels of context" proposed by Schimmelpfennig et al. (2025), organizing contextual variables into individual, organizational, and sociogeographical dimensions. To examine sampling and participant description practices, this coding also captured whether sampling methods were explicitly reported, the types of sampling employed, and the use of survey platforms. Referencing Johns' (2006) discussion of decontextualization in organizational research and the APA JARS (Appelbaum et al. 2018), which emphasize thorough reporting of participant characteristics, we operationally distinguished the three contextual levels and used them to rate the specificity of participant and organizational descriptions in each article. Excluding basic bibliographic information, the coding framework covered 29 conceptual dimensions operationalized into 46 analytical coding variables (see Supplementary Table S1 for the analytical framework and operational coding criteria).

Data extraction and validity assurance

This study's use of generative artificial intelligence (AI) followed the guidelines for responsible AI use in nonempirical HRD research proposed by Crocco et al. (2026), which restrict AI to legitimate supporting roles that preserve researchers' intellectual agency and require explicit disclosure of its purpose and scope. Accordingly, we employed API-based structured data extraction alongside procedures designed to maintain human oversight and control, as detailed below.

Technical pipeline and extraction mechanisms

To systematically extract contextual data from a large body of empirical literature, we implemented an API-based pipeline using Google's Gemini-2.5-flash large language model using Python, applying three technical controls. First, the full-text PDF of each article was provided directly to the model, using its long context window to avoid the loss of contextual information that could result from relying solely on abstracts or selected passages. Second, the temperature parameter was fixed at 0.0 to minimize variation in generated outputs and support reproducibility, and the model was instructed to extract only information explicitly stated in the source text. Third, a strict Pydantic-based JSON schema was defined to enforce structural consistency in the extracted data. Predefined enumerated categories, Boolean fields, and numeric data types were programmatically enforced.

Human-in-the-loop verification and researcher accountability

As Crocco et al. (2026) emphasized, AI cannot assume responsibility for research validity or scholarly rigor. Therefore, we implemented a multistage verification procedure whereby we retained full responsibility throughout. First, pilot coding was conducted on three randomly selected articles to assess extraction accuracy. Discrepancies in variables involving multiple contextual dimensions, such as organizational type and industry classification, led us to refine the coding categories, extraction schema, and coding rules through discussion before the main extraction. Second, the pipeline was configured to

flag cases that required additional review because of ambiguity or overlapping contextual information and record an explanatory memo for each flagged case. After coding, flagged records were subjected to targeted reextraction, manually checked against the full texts, and reconciled through researcher agreement. Of the 338 sample units, 44 were flagged and reviewed, representing approximately 13.0% of the total. Corrections were made to 10 of these units, which concerned participants' mean age calculation, the coding of studies using thematic qualitative data analysis, missing coding entries, and descriptive specificity ratings. Finally, we cross-checked the key bias variables—WEIRD-country status, large corporation or MNC status, managerial inclusion, and white-collar inclusion—against the source articles for all 338 sample units, including those not flagged by the AI. We also examined the full texts of the 11 multi-sample articles (8 from *HRDQ* and 3 from *HRDI*) to verify their separation into 23 units of analysis.

Analytical strategy

Descriptive statistics, cross-tabulations, and latent class analysis (LCA) were used to examine the contexts of the research populations represented in the 338 empirical sample units. Descriptive statistics and cross-tabulations were conducted using IBM SPSS Statistics 29.0, and LCA was performed using Mplus 6.0 (Muthén and Muthén 2011). First, frequencies, percentages, and cross-tabulations were generated for the individual, organizational, and sociogeographical variables listed in Supplementary Table S1. Second, LCA was used to identify the empirical configurations of research population bias across multiple contextual dimensions. Moving beyond separate frequency distributions for individual dimensions, we adopted a study-centered approach to examine how the characteristics of knowledge producers and the populations they study combine into distinct patterns within empirical research. Five indicators were included to capture the distribution of power in knowledge production and the multilevel contexts of workplace samples—first-author affiliation with an institution in a WEIRD country; the WEIRD status of the country from which the sample was drawn; inclusion of large, multinational, or large public sector organizations; inclusion of employees in clerical, managerial, or professional occupations; and inclusion of managerial perspectives. Models specifying one through five latent classes were estimated sequentially. The number of classes was selected by considering statistical fit and theoretical interpretability (Masyn 2013; Nylund et al. 2007). Specifically, reductions in the Akaike information criterion (AIC) and Bayesian information criterion (BIC) were examined first to assess the balance between model fit and parsimony. Entropy was considered as an indicator of classification precision, alongside a minimum class size of 5% of the total sample and the substantive meaningfulness of the resulting classes (Masyn 2013).

Results

General characteristics of the included articles

Distribution by publication year and journal

Of the 338 empirical sample units, 160 (47.34%) were drawn from *HRDQ* and 178 (52.66%) from *HRDI*, comprising 151 and 175 unique articles, respectively. Annual sample counts ranged from 23 in 2017 to 46 in 2021, averaging approximately 34 per year (Supplementary Table S2).

Methodological approaches and research designs

Quantitative research accounted for the largest share of the sample units analyzed (47.93%, n = 162), followed by qualitative (43.20%, n = 146) and mixed methods research (8.87%, n = 30). Multilevel data were incorporated in 16.0% of quantitative (n = 26) and 10.0% of mixed methods sample units (n = 3), and experimental designs were used in 12.3% (n = 20) and 20.0% (n = 6), respectively, with quasi-experimental (n = 16) and pre–post designs (n = 6) more common than randomized controlled trials (n = 4). Analytical software was not reported in 64.4% of qualitative (n = 94), 56.7% of mixed methods (n = 17), and 27.2% of quantitative sample units (n = 44). Table 2 provides a detailed breakdown by methodological approach.

Table 2

Methodological Characteristics, Research Designs, and Analytical Profiles

Methodological Orientation	No. of Sample Units (%)	Sample Size *M* (*Mdn*)	Multilevel Data, *n* (%)	Experimental Design, *n* (%)	Software Not Reported, *n* (%)	Primary Software Reported (Ranked)
Quantitative	162 (47.9%)	1,063.7 (173.5)	26 (16.0%)	20 (12.3%)	44 (27.2%)	1. SPSS (17.9%, n = 29) 2. Mplus (14.8%, n = 24) 3. R (9.3%, n = 15) 4. AMOS (8.6%, n = 14)
Qualitative	146 (43.2%)	51.2 (21.0)	N/A	N/A	94 (64.4%)	1. NVivo (21.9%, n = 32) 2. ATLAS.ti (5.5%, n = 8) 3. MAXQDA (2.1%, n = 3)
Mixed Methods	30 (8.9%)	597.6 (227.0)	3 (10.0%)	6 (20.0%)	17 (56.7%)	1. Mplus (13.3%, n = 4) 2. ATLAS.ti (6.7%, n = 2) 3. SPSS/AMOS/NVivo (each 3.3%, n = 1)

Note. $N = 338$ sample units. Percentages in the sample units column are based on the full sample, and all other percentages are based on the number of sample units within each methodological approach. *M* = mean; *Mdn* = median; N/A = not applicable.

Who is studied in AHRD-affiliated empirical HRD research, and in what contexts?

Individual-level research sample composition

To examine research population biases at the individual level, frequencies and percentages for categories of gender, age, educational attainment, employment status, hierarchical position, occupation, and diversity-related and potentially vulnerable sample characteristics—covering disability, race/ethnicity, sexual orientation, and student sample status—were cross-tabulated by methodological approach. The results are presented in Table 3.

Table 3

Individual-Level Contextual Characteristics by Methodological Approach

Variable and Category	Quantitative (*n* = 162)	Qualitative (*n* = 146)	Mixed Methods (*n* = 30)	Total (*N* = 338)
Gender composition (% male)				
>75%	23 (14.2%)	13 (8.9%)	2 (6.7%)	38 (11.2%)
>50%–75%	55 (34.0%)	28 (19.2%)	6 (20.0%)	89 (26.3%)
>25%–50%	47 (29.0%)	29 (19.9%)	7 (23.3%)	83 (24.6%)

Variable and Category	Quantitative (*n* = 162)	Qualitative (*n* = 146)	Mixed Methods (*n* = 30)	Total (*N* = 338)
0%–25%	11 (6.8%)	22 (15.1%)	2 (6.7%)	35 (10.4%)
Not stated	26 (16.0%)	54 (37.0%)	13 (43.3%)	93 (27.5%)
Age reporting				
Mean age reported	82 (50.6%)	17 (11.6%)	10 (33.3%)	109 (32.2%)
Age range reported	41 (25.3%)	41 (28.1%)	10 (33.3%)	92 (27.2%)
Mixed ages, unspecified	11 (6.8%)	26 (17.8%)	1 (3.3%)	38 (11.2%)
Not stated	28 (17.3%)	62 (42.5%)	9 (30.0%)	99 (29.3%)
Educational attainment				
University graduates only	48 (29.6%)	65 (44.5%)	17 (56.7%)	130 (38.5%)
Mixed educational levels	56 (34.6%)	14 (9.6%)	5 (16.7%)	75 (22.2%)
High school or below	4 (2.5%)	1 (0.7%)	0 (0.0%)	5 (1.5%)
Not stated	54 (33.3%)	66 (45.2%)	8 (26.7%)	128 (37.9%)
Employment status				
Regular employment only	83 (51.2%)	99 (67.8%)	12 (40.0%)	194 (57.4%)
Mixed (regular and nonregular)	13 (8.0%)	20 (13.7%)	5 (16.7%)	38 (11.2%)
Other (e.g., self-employed)	1 (0.6%)	1 (0.7%)	3 (10.0%)	5 (1.5%)
Not stated	65 (40.1%)	26 (17.8%)	10 (33.3%)	101 (29.9%)
Hierarchical position				
Managers/executives only	20 (12.3%)	39 (26.7%)	3 (10.0%)	62 (18.3%)
Mixed (managers and staff)	63 (38.9%)	86 (58.9%)	19 (63.3%)	168 (49.7%)
Nonmanagerial staff only	38 (23.5%)	8 (5.5%)	2 (6.7%)	48 (14.2%)
Not stated	41 (25.3%)	13 (8.9%)	6 (20.0%)	60 (17.8%)
Occupational category				
White-collar/professional	120 (74.1%)	113 (77.4%)	22 (73.3%)	255 (75.4%)
Pink-collar/service/sales/ healthcare	6 (3.7%)	6 (4.1%)	0 (0.0%)	12 (3.6%)
Blue-collar/trades/production	5 (3.1%)	0 (0.0%)	1 (3.3%)	6 (1.8%)
Mixed occupations	28 (17.3%)	21 (14.4%)	6 (20.0%)	55 (16.3%)
Not stated	3 (1.9%)	6 (4.1%)	1 (3.3%)	10 (3.0%)
Disability status				
Reported	3 (1.9%)	0 (0.0%)	0 (0.0%)	3 (0.9%)
Not stated	159 (98.1%)	146 (100.0%)	30 (100.0%)	335 (99.1%)
Race/ethnicity				
Reported	45 (27.8%)	37 (25.3%)	8 (26.7%)	90 (26.6%)
Not stated	117 (72.2%)	109 (74.7%)	22 (73.3%)	248 (73.4%)
Sexual orientation				
Reported	3 (1.9%)	2 (1.4%)	0 (0.0%)	5 (1.5%)
Not stated	159 (98.1%)	144 (98.6%)	30 (100.0%)	333 (98.5%)
Student sample				
Undergraduate/graduate student sample	19 (11.7%)	20 (13.7%)	1 (3.3%)	40 (11.8%)
Nonstudent sample	143 (88.3%)	126 (86.3%)	29 (96.7%)	298 (88.2%)

Note. Values are sample unit frequencies with percentages in parentheses. Percentages are calculated within each methodological

approach, and those in the total column are based on all 338 sample units. “Not stated” indicates that the relevant information was not reported.

Regarding gender, samples in which female participants dominated (men 0%–25%) accounted for 15.1% of qualitative sample units (n = 22), representing more than twice the proportion observed in quantitative research (6.8%, n = 11). This indicates a greater prevalence of female-dominated samples in qualitative research. Gender composition was not reported in 37.0% of qualitative sample units (n = 54), compared with 16.0% of quantitative sample units (n = 26). Mean age was reported for only 32.2% of all sample units (n = 109). In qualitative research, 17.8% provided only an unspecified description of mixed ages and 42.5% provided no age information, leaving 60.3% without clearly specified age characteristics. Among the 109 sample units that reported mean age, 52.3% (n = 57) had mean ages between 25 and 40 years and 38.5% (n = 42) between 41 and 65 years. These categories accounted for 90.8% of sample units reporting mean age, and none reported a mean age above 65 years.

Patterns of employment status and diversity revealed a concentration in mainstream labor market groups and limited representation or reporting of minority characteristics. Samples exclusively consisting of regular employees accounted for 57.4% of all sample units (n = 194), whereas employment status was not reported in 40.1% of quantitative sample units (n = 65). Samples exclusively consisting of managers (18.3%, n = 62) and those with managers and nonmanagerial staff (49.7%, n = 168), accounting for 68.0% of all sample units (n = 230). In contrast, samples exclusively consisting of nonmanagerial staff represented 14.2% (n = 48), falling to 5.5% within qualitative research. Among the 210 sample units reporting educational attainment, 61.9% (n = 130) exclusively consisted of participants with a university degree or higher, while an additional 35.7% (n = 75) examined samples with mixed educational backgrounds (frequently including college-educated workers). Samples exclusively consisting of workers with a high school education or below only accounted for 2.4% of reporting units (n = 5, or 1.5% of all sample units). Regarding occupation, clerical, managerial, and professional samples dominated, accounting for 75.4% (n = 255). Samples exclusively consisting of production, skilled trade, or manual workers such as factory workers, craft workers, and farmers only accounted for 1.8% of the 338 sample units (n = 6). Disability status and sexual orientation were rarely reported, appearing in only 0.9% (n = 3) and 1.5% (n = 5) of sample units, respectively. Student samples accounted for 11.8% (n = 40).

Organization-level research sample composition

Organization-level contexts were examined through cross-tabulations using a methodological approach across organization type, industry, governance structure, and size variables. The results are presented in Table 4.

Table 4

Organizational-Level Contextual Characteristics by Methodological Approach

Variable and Category	Quantitative (n = 162)	Qualitative (n = 146)	Mixed Methods (n = 30)	Total (N = 338)
Organization type				
Private for-profit firms	89 (54.9%)	52 (35.6%)	8 (26.7%)	149 (44.1%)

Variable and Category	Quantitative (*n* = 162)	Qualitative (*n* = 146)	Mixed Methods (*n* = 30)	Total (*N* = 338)
Universities and other educational institutions	21 (13.0%)	26 (17.8%)	8 (26.7%)	55 (16.3%)
Public/government	14 (8.6%)	17 (11.6%)	5 (16.7%)	36 (10.7%)
Healthcare/hospital	9 (5.6%)	7 (4.8%)	0 (0.0%)	16 (4.7%)
Nonprofit/NGO	2 (1.2%)	9 (6.2%)	1 (3.3%)	12 (3.6%)
Mixed sectors	2 (1.2%)	13 (8.9%)	2 (6.7%)	17 (5.0%)
Not stated	25 (15.4%)	22 (15.1%)	6 (20.0%)	53 (15.7%)
Industry classification				
Cross/multiindustry	70 (43.2%)	56 (38.4%)	14 (46.7%)	140 (41.4%)
Public administration & defense	22 (13.6%)	28 (19.2%)	6 (20.0%)	56 (16.6%)
Manufacturing & engineering	16 (9.9%)	11 (7.5%)	0 (0.0%)	27 (8.0%)
Healthcare services	8 (4.9%)	8 (5.5%)	1 (3.3%)	17 (5.0%)
Services, retail & hospitality	8 (4.9%)	2 (1.4%)	1 (3.3%)	11 (3.3%)
IT & software services	5 (3.1%)	7 (4.8%)	1 (3.3%)	13 (3.8%)
Finance & insurance	7 (4.3%)	7 (4.8%)	1 (3.3%)	15 (4.4%)
Social welfare & nonprofit services	1 (0.6%)	8 (5.5%)	0 (0.0%)	9 (2.7%)
Energy & chemicals	3 (1.9%)	1 (0.7%)	1 (3.3%)	5 (1.5%)
Educational services	2 (1.2%)	3 (2.1%)	1 (3.3%)	6 (1.8%)
Other single industry	7 (4.3%)	11 (7.5%)	3 (10.0%)	21 (6.2%)
Not stated	13 (8.0%)	4 (2.7%)	1 (3.3%)	18 (5.3%)
Governance structure				
Private enterprise (unlisted)	45 (27.8%)	39 (26.7%)	4 (13.3%)	88 (26.0%)
State-owned/public organization	22 (13.6%)	34 (23.3%)	8 (26.7%)	64 (18.9%)
Mixed governance	17 (10.5%)	26 (17.8%)	6 (20.0%)	49 (14.5%)
Family business	3 (1.9%)	4 (2.7%)	0 (0.0%)	7 (2.1%)
Publicly listed corporation	5 (3.1%)	2 (1.4%)	0 (0.0%)	7 (2.1%)
Nonprofit/cooperative	3 (1.9%)	2 (1.4%)	1 (3.3%)	6 (1.8%)
Not stated	67 (41.4%)	39 (26.7%)	11 (36.7%)	117 (34.6%)
Organization size				
Large corporations & MNCs	53 (32.7%)	55 (37.7%)	10 (33.3%)	118 (34.9%)
Large public organizations/universities/hospitals	16 (9.9%)	24 (16.4%)	5 (16.7%)	45 (13.3%)
Midsized enterprises & SMEs (<500 employees)	12 (7.4%)	14 (9.6%)	2 (6.7%)	28 (8.3%)
Mixed sizes	11 (6.8%)	14 (9.6%)	1 (3.3%)	26 (7.7%)
Not stated	70 (43.2%)	39 (26.7%)	12 (40.0%)	121 (35.8%)

Note. Values are sample unit frequencies with percentages in parentheses. Percentages are calculated within each methodological approach, and those in the total column are based on all 338 sample units. "Not stated" indicates that the relevant information was not reported. IT = information technology; MNC = multinational corporation; SME = small and medium-sized enterprise.

Private, for-profit firms accounted for the largest share of sample units (44.1%, *n* = 149), rising to 54.9% within quantitative research. Universities and other educational institutions (16.3%) and public sector and government organizations (10.7%) followed. In contrast, nonprofit organizations and nongovernmental organizations accounted for only 3.6% of sample units (*n* = 12). Regarding industry, samples spanning

multiple industries constituted the largest category (41.4%, n = 140), indicating a prevalence of sampling across industrial settings rather than within a specific industry context. Among single-industry samples, public administration and defense accounted for the largest share (16.6%, n = 56), whereas manufacturing and engineering, traditionally prominent settings for HRD research, accounted for 8.0% (n = 27). Governance structures were concentrated in privately held firms (26.0%) and state-owned and public organizations (18.9%), and governance information was not reported in 34.6% of all sample units (n = 117). Large organizations accounted for 48.2% of all sample units (n = 163), comprised of large private corporations and MNCs (34.9%, n = 118) and large public sector organizations, including public universities and general hospitals (13.3%, n = 45). In contrast, medium-sized, small, and microenterprises were represented in only 8.3% of sample units (n = 28). Organization size was not reported in 35.8% of all sample units, rising to 43.2% within quantitative research.

Sociogeographical-level research samples composition

To examine research population bias at societal and national levels, WEIRD-country representation, cross-national comparative design, substantive cultural context integration, and geographical distribution were cross-tabulated using a methodological approach. The results are presented in Table 5.

Table 5

Sociogeographical Contextual Characteristics by Methodological Approach

Variable and Category	Quantitative (n = 162)	Qualitative (n = 146)	Mixed Methods (n = 30)	Total (N = 338)
WEIRD country representation				
WEIRD country data	75 (46.3%)	92 (63.0%)	19 (63.3%)	186 (55.0%)
Non-WEIRD country data	87 (53.7%)	54 (37.0%)	11 (36.7%)	152 (45.0%)
Geographic scope of research				
Single-country design	135 (83.3%)	118 (80.8%)	27 (90.0%)	280 (82.8%)
Cross-national comparative design	19 (11.7%)	26 (17.8%)	3 (10.0%)	48 (14.2%)
Not stated	8 (4.9%)	2 (1.4%)	0 (0.0%)	10 (3.0%)
Cultural contextualization				
Substantively integrated	99 (61.1%)	99 (67.8%)	19 (63.3%)	217 (64.2%)
Country names only	56 (34.6%)	41 (28.1%)	10 (33.3%)	107 (31.7%)
Not stated	7 (4.3%)	6 (4.1%)	1 (3.3%)	14 (4.1%)
Geographical distribution				
Europe	42 (25.9%)	44 (30.1%)	9 (30.0%)	95 (28.1%)
North America	37 (22.8%)	37 (25.3%)	9 (30.0%)	83 (24.6%)
Asia (East, South, Southeast)	57 (35.2%)	18 (12.3%)	4 (13.3%)	79 (23.4%)
Middle East	7 (4.3%)	8 (5.5%)	0 (0.0%)	15 (4.4%)
Africa	1 (0.6%)	10 (6.8%)	4 (13.3%)	15 (4.4%)
Oceania	2 (1.2%)	6 (4.1%)	1 (3.3%)	9 (2.7%)
South America	2 (1.2%)	4 (2.7%)	0 (0.0%)	6 (1.8%)
Multiple continents	10 (6.2%)	15 (10.3%)	3 (10.0%)	28 (8.3%)
Other	1 (0.6%)	1 (0.7%)	0 (0.0%)	2 (0.6%)
Not stated	3 (1.9%)	3 (2.1%)	0 (0.0%)	6 (1.8%)

Note. Values are sample unit frequencies with percentages in parentheses. Percentages are calculated within each methodological approach, and those in the total column are based on all 338 sample units. For cultural contextualization, "not stated" indicates that neither the country nor its cultural context was reported. WEIRD = Western, educated, industrialized, rich, and democratic.

Overall, 55.0% of the empirical sample units (n = 186) were based on data collected in WEIRD countries. This proportion varied considerably by methodological approach. WEIRD-country samples accounted for more than 60% of qualitative (63.0%) and mixed methods (63.3%) sample units. In contrast, non-WEIRD-country samples constituted a majority of quantitative sample units (53.7%, n = 87), which may reflect the prevalence of quantitative studies drawing on large-scale survey data from East Asia and developing countries. Geographically, Europe (28.1%, n = 95) and North America (24.6%, n = 83) accounted for 52.7% of all sample units, indicating a concentration in Western regions. Asia followed at 23.4% (n = 79), and the Middle East (4.4%), Africa (4.4%), Oceania (2.7%), and South America (1.8%) accounted for substantially smaller shares. Single-country samples dominated, accounting for 82.8% of all sample units (n = 280), whereas cross-national comparative designs only represented 14.2% (n = 48). Furthermore, 31.7% of sample units (n = 107) were solely described by naming the countries of data collection, without substantively connecting the specific cultural contexts of those societies to the theoretical or empirical aspects of the research.

Research population bias configurations

LCA was conducted to examine how the five indicators described in the Analytical strategy section—capturing knowledge producers and research population contexts—combine in AHRD-affiliated empirical HRD research to form distinct patterns of knowledge production. Models specifying one through five latent classes were compared sequentially (Table 6).

Table 6

Model Fit and Class Distributions for Latent Class Models (N = 338)

No. of classes	Log-Likelihood (LL)	AIC	BIC	SABIC	Entropy	Class size, *n* (%)				
						1	2	3	4	5
1	−1,057.42	2,124.85	2,143.96	2,128.10	1.000	338 (100.0)	-	-	-	-
2	−1,009.22	2,040.44	2,082.49	2,047.60	1.000	186 (55.0)	152 (45.0)	-	-	-
3	−1,002.57	2,039.14	2,104.13	2,050.20	0.863	182 (53.8)	125 (37.0)	31 (9.2)	-	-
4a	−998.40	2,042.80	2,130.73	2,057.77	0.728	183 (54.1)	51 (15.1)	52 (15.4)	52 (15.4)	-
5	−996.58	2,051.17	2,162.03	2,070.04	0.876	147 (43.5)	85 (25.1)	52 (15.4)	34 (10.1)	20 (5.9)

Note. Models were estimated in Mplus 6.0 using maximum likelihood estimation with robust standard errors (MLR), with STARTS set to 200 40. AIC = Akaike information criterion; BIC = Bayesian information criterion; SABIC = sample-size adjusted Bayesian information criterion. Class membership frequencies are based on assignment to the class with the highest posterior probability. Dashes indicate that the corresponding class is not present in the model. a Selected Model

The four-class solution was selected on substantive interpretive grounds, considered alongside the information criteria and an entropy value of .728. Although this solution did not yield the lowest AIC or BIC, it provided a more differentiated account of the configurations linking knowledge producers with the national, organizational, occupational, and hierarchical research population contexts. The conditional response probabilities and characteristics of the four classes are presented in Table 7.

Table 7

Latent Class Profiles and Conditional Indicator Probabilities (Optimal 4-Class Model)

Indicator Variable	Overall proportion (*N* = 338)	Class 1: Western Managerial (*n* = 183, 54.1%)	Class 2: Non-Western SME Diverse (*n* = 51, 15.1%)	Class 3: Western SME Nonmanagerial Staff (*n* = 52, 15.4%)	Class 4: Non-Western Large Corporate-Managerial (*n* = 52, 15.4%)
First Author WEIRD Affiliation	.749	.967	.141	1.000	.437
Data Collection Country WEIRD Status	.550	.799	.061	.620	.064
Large-Scale/MNC Organization	.482	.484	.317	.257	1.000
White-Collar/Professional Occupation	.754	.675	.735	1.000	.940
Managerial Hierarchy Inclusion	.680	.791	.581	.000	1.000

Note. Conditional probabilities represent the probability of an indicator being coded 1, given membership in that latent class.

Class 1, labeled Western Managerial, comprised 54.1% of the sample units (*n* = 183). This class exhibited high conditional probabilities of first-author affiliation with a Western institution (96.7%), data collection in a Western country (79.9%), and managerial inclusion (79.1%). Therefore, it represented a prominent configuration of WEIRD-oriented knowledge production, in which researchers affiliated with Western institutions predominantly studied Western populations and incorporated managerial perspectives. Class 2, labeled Non-Western SME-Diverse, accounted for just 15.1% of the sample units (*n* = 51). The conditional probabilities of first-author WEIRD affiliation and WEIRD-country data were low, at 14.1% and 6.1%, respectively, indicating a concentration of researchers affiliated with non-WEIRD institutions studying non-WEIRD populations. The probability of large-organization inclusion was also relatively low (31.7%), suggesting greater visibility of a wider range of workplaces in non-Western contexts. Class 3, labeled Western SME Nonmanagerial Staff, comprised 15.4% of the sample units (*n* = 52). This class was characterized by first-author affiliation from Western institutions (100.0%), a relatively low probability of large-organization inclusion (25.7%), and a zero estimated probability of managerial inclusion. Class 4, labeled Non-Western Large Corporate-Managerial, accounted for 15.4% of the sample units (*n* = 52) and highlighted a particularly salient configuration of research population bias. The conditional probability of non-WEIRD-country data was 93.6%, while the probabilities of large-organization and managerial inclusion were both 100.0%. The probability of first-author affiliation with a Western institution was 43.7%. This configuration indicates that extending research to non-WEIRD countries does not necessarily diversify its organizational or hierarchical focus. Instead, research in these settings may remain concentrated in large organizations and managerial perspectives, raising questions about whose experiences become visible across international knowledge production.

Classification quality was assessed using the average posterior class membership probabilities (see Supplementary Table S3 for the complete classification probability matrix). Western Managerial and Non-Western SME-Diverse classes together accounted for 69.2% of the sample units (*n* = 234) and had

respective average posterior probabilities of .907 and .936, indicating a comparatively clear classification. Western SME Nonmanagerial Staff and Non-Western Large Corporate-Managerial classes had lower average posterior probabilities of .637 and .642, respectively, indicating greater classification uncertainty.

This uncertainty may reflect overlap in the contextual characteristics captured by the indicators. Sample units assigned to the Western SME Nonmanagerial Staff class had an average posterior probability of .309 of belonging to the Western Managerial class, consistent with their shared Western institutional and geographical characteristics, whereas those assigned to the Non-Western Large Corporate-Managerial class had probabilities of .197 for the Western Managerial class and .161 for the Non-Western SME-Diverse class, indicating a hybrid configuration combining a non-WEIRD data orientation with a strong managerial and large-organization focus. Although the average posterior probabilities for Classes 3 and 4 fell below the .70 benchmark referenced in this study, the overall entropy of .728 and the contrasting conditional response profiles—particularly the absence of managerial inclusion in Class 3 versus its estimated probability of 1.000 in Class 4—supported the substantive interpretability of the four-class solution, while classification uncertainty in the two classes warrants caution when interpreting their profiles (Bauer and Curran 2003; Nagin 2005).

How do researchers treat research populations in AHRD-affiliated empirical HRD research?

Reporting of sampling methods and types

Sampling methods were reported for 95.0% of the empirical sample units (n = 321). Convenience (41.4%) and purposive (32.0%) sampling were particularly prevalent, accounting for 73.4% of all sample units. Cross-tabulation by methodological approach revealed marked differences in sampling patterns. In quantitative research (n = 162), convenience sampling dominated (67.3%, n = 109), whereas random, stratified, and cluster probability sampling only accounted for 9.9% (n = 16). In qualitative research (n = 146), purposive sampling was the most common approach (62.3%, n = 91), followed by mixed purposive-convenience sampling (14.4%, n = 21), and convenience sampling (13.0%, n = 19). The "other" category included secondary analyses of publicly available panel data, autoethnographic studies, and behavioral experiments. Sampling methods were not reported for 5.0% of all sample units (n = 17). Table 8 presents the distribution of sampling types by methodological approach.

Table 8

Cross-Tabulation of Sampling Typologies Across Methodological Orientations

Sampling Typology	Quantitative (n = 162)	Qualitative (n = 146)	Mixed Methods (n = 30)	Total (N = 338)
Convenience sampling	109 (67.3%)	19 (13.0%)	12 (40.0%)	140 (41.4%)
Purposive sampling	9 (5.6%)	91 (62.3%)	8 (26.7%)	108 (32.0%)
Mixed sampling	7 (4.3%)	21 (14.4%)	8 (26.7%)	36 (10.7%)
Probability sampling	16 (9.9%)	1 (0.7%)	0 (0.0%)	17 (5.0%)
Snowball sampling	2 (1.2%)	6 (4.1%)	0 (0.0%)	8 (2.4%)
Quota sampling	2 (1.2%)	0 (0.0%)	0 (0.0%)	2 (0.6%)
Other (autoethnography, etc.)	6 (3.7%)	3 (2.1%)	1 (3.3%)	10 (3.0%)
Not stated	11 (6.8%)	5 (3.4%)	1 (3.3%)	17 (5.0%)

Sampling Typology	Quantitative (n = 162)	Qualitative (n = 146)	Mixed Methods (n = 30)	Total (N = 338)
Total	162 (100.0%)	146 (100.0%)	30 (100.0%)	338 (100.0%)

Note. Values are sample unit frequencies with percentages in parentheses. Percentages are calculated within each methodological approach, and those in the total column are based on all 338 sample units. "Not stated" indicates that the sampling method was not reported.

Specificity of individual and organizational descriptions

We assessed the specificity of individual and organizational descriptions to examine how concretely individuals and their organizational contexts were represented in the articles. Each dimension was rated at low (1), medium (2), or high (3) levels. Level 1 denoted abstract descriptions using generic nouns. Level 2 denoted limited, one-dimensional descriptions, such as basic demographic information or the industry in which individuals worked. Level 3 denoted detailed, multidimensional descriptions incorporating substantive job roles, employment structures, and organizational characteristics. These ratings provide a quantitative assessment of the contextual richness of descriptions in empirical articles. Table 9 presents the distribution of specificity ratings.

Table 9

Specificity Ratings for Individual and Organizational Descriptions

Specificity Rating Level	Individual Specificity, n (%)	Organizational Specificity, n (%)
Level 1 (Low/Abstract generalization)	24 (7.10%)	39 (11.54%)
Level 2 (Medium/Flat categorical description)	171 (50.59%)	174 (51.48%)
Level 3 (High/Multidimensional rich context)	143 (42.31%)	125 (36.98%)
Overall Mean Score	2.35	2.25

Note. N = 338 sample units. Ratings range from 1 (low specificity) to 3 (high specificity).

Individual and organizational description specificity ratings were cross-tabulated to examine their joint distribution (Table 10). The most frequent combination for both dimensions was medium specificity, accounting for 34.02% of all sample units (n = 115). In this group, descriptions of individuals and organizations remained limited to broad categories or basic contextual attributes. High specificity on both dimensions was observed in 26.63% of sample units (n = 90), indicating multidimensional descriptions of individuals and organizational contexts. By contrast, low specificity on both dimensions accounted for 3.55% (n = 12) and was primarily observed in quantitative research using secondary large-scale panel data or longitudinal surveys.

Table 10

Cross-Tabulation of Individual and Organizational Description Specificity

Individual Specificity Level	Organizational Specificity Level	Total (N = 338)		
	Level 1 (Low)	Level 2 (Medium)	Level 3 (High)	
Level 1 (Low)	12 (3.55%)	10 (2.96%)	2 (0.59%)	24 (7.10%)
Level 2 (Medium)	23 (6.80%)	115 (34.02%)	33 (9.76%)	171 (50.59%)

Individual Specificity Level	Organizational Specificity Level	Total (N = 338)		
Level 3 (High)	4 (1.18%)	49 (14.50%)	90 (26.63%)	143 (42.31%)
Total	39 (11.54%)	174 (51.48%)	125 (36.98%)	338 (100.0%)

Note. Values are sample unit frequencies with percentages in parentheses. All percentages are based on the full sample of 338 units. Rows represent the specificity of individual descriptions, and columns represent the specificity of organizational descriptions.

Contextual information deficits

To assess the completeness of contextual reporting in our empirical HRD research sample, we also examined information deficits across key individual, organizational, and societal variables using a methodological approach (Table 11). Overall, 87.6% of sample units (n = 296) exhibited deficits in two or more core contextual variables of gender, age, employment status, educational attainment, occupation, organization size, and cultural background. Information deficits were pervasive across all methodological traditions, occurring in 87.0% of quantitative studies (n = 141), 87.0% of qualitative studies (n = 127), and 93.3% of mixed methods studies (n = 28), demonstrating that incomplete contextual reporting was widespread across the contemporary empirical HRD literature.

Basic demographic characteristics were reported relatively consistently in quantitative research, with nonreporting rates of 16.0% for gender and 17.3% for age, potentially reflecting their use as control variables. In contrast, nonreporting rates exceeded 40% for organization size (43.2%) and employment status (40.1%). In qualitative research, gender was not reported for 37.0% of sample units (n = 54), and age information was absent for 42.5% (n = 62). These omissions may partially reflect participant protection practices in small-sample qualitative studies, where withholding identifying information preserves anonymity.

Table 11

Cross-Tabulation of Contextual Information Deficits Across Methodologies

Contextual Information Dimension	Quantitative (n = 162)	Qualitative (n = 146)	Mixed Methods (n = 30)	Total Deficit N (%)
1. [Individual] Disability status	159 (98.1%)	146 (100.0%)	30 (100.0%)	335 (99.1%)
2. [Individual] Sexual orientation	159 (98.1%)	144 (98.6%)	30 (100.0%)	333 (98.5%)
3. [Individual] Race/ethnicity	117 (72.2%)	109 (74.7%)	22 (73.3%)	248 (73.4%)
4. [Individual] Education level	54 (33.3%)	66 (45.2%)	8 (26.7%)	128 (37.9%)
5. [Societal] Cultural context integration	63 (38.9%)	47 (32.2%)	11 (36.7%)	121 (35.8%)
6. [Organizational] Organization size	70 (43.2%)	39 (26.7%)	12 (40.0%)	121 (35.8%)
7. [Individual] Employment status	65 (40.1%)	26 (17.8%)	10 (33.3%)	101 (29.9%)
8. [Individual] Age group	28 (17.3%)	62 (42.5%)	9 (30.0%)	99 (29.3%)
9. [Individual] Gender composition	26 (16.0%)	54 (37.0%)	13 (43.3%)	93 (27.5%)
10. [Individual] Occupational category	2 (1.2%)	2 (1.4%)	1 (3.3%)	5 (1.5%)
Two or more contextual information deficits	**141 (87.0%)**	**127 (87.0%)**	**28 (93.3%)**	**296 (87.6%)**

Note. Values are sample unit frequencies with percentages in parentheses. Percentages are calculated within each methodological approach, and those in the total column are based on all 338 sample units. The first three variables concern minority identities

and yield overall nonreporting rates exceeding 70%. For cultural contextualization, deficits include both geographical or country-name listing without substantive cultural integration and the complete absence of country or cultural information.

Discussion

This study examined how research subjects and their contexts were represented in 326 empirical articles, comprising 338 sample units, published in Human Resource Development Quarterly and Human Resource Development International from 2016 to 2025. Three findings warrant discussion. First, research attention within this bounded corpus was concentrated in particular occupational, organizational, and geographical settings. Second, the latent class analysis (LCA) suggested that these characteristics were patterned together, rather than varying independently. Third, reporting a sampling method did not necessarily coincide with sufficiently detailed information about the people and settings studied. Together, these findings extend the question raised by the WEIRD debate—from where evidence originates to whose work experiences it reflects and how transparently those experiences are situated.

Beyond WEIRD: Multidimensional patterns of sample diversity

The WEIRD critique draws attention to the limitations of relying disproportionately on evidence originating in Western, educated, industrialized, rich, and democratic societies (Henrich et al. 2010). The present findings suggest that national location alone provides an incomplete description of the empirical settings represented in these two HRD journals. In the sample units examined, managerial perspectives (68.0%), white-collar occupational groups (75.4%), and large organizations (48.2%) featured prominently, while blue-collar groups (1.8%) and small and medium-sized enterprises (8.3%) appeared much less frequently. These distributions describe the concentration of published research attention; they do not, by themselves, establish that an individual study sampled inappropriately relative to its intended population.

The four-class LCA provides an exploratory account of how selected characteristics co-occurred. The Western-Managerial profile (Class 1, 54.1%) was the largest, but the Non-Western Large Corporate-Managerial profile (Class 4, 15.4%) is particularly instructive. Its presence indicates that a non-WEIRD national setting does not necessarily entail occupational or organizational diversity. Conversely, the Non-Western SME-Diverse profile (Class 2, 15.1%) points to a different combination of organizational and geographical settings within the corpus. These class labels summarize model-estimated patterns across five indicators; they are not measures of the representativeness, quality, or cultural orientations of the individual studies assigned to them.

Examples from the analyzed corpus—from military academic education in Eritrea (Ogbamariam and Teklemariam 2017) and Brazilian social enterprises (Rodriguez et al. 2023) to training and apprenticeship systems in Ghana (Ayentimi et al. 2018)—illustrate the range of development contexts that can become visible when researchers look beyond frequently studied corporate settings. Their value lies not in proving that one latent class generates better theory than another, but in drawing attention to potentially different developmental questions and institutional conditions. The multidimensional levels-of-context framework used here offers a way to examine such differences without reducing sample diversity to a WEIRD/non-WEIRD binary.

Sample diversity and the contextual boundaries of HRD knowledge

Concentration of evidence in particular samples matters because HRD theories and interventions are often interpreted and applied beyond the circumstances in which the underlying studies were conducted. Evidence from employees in large multinational corporations, for example, may address developmental resources and constraints that differ from those of workers in smaller organizations. As Stewart and Beaver (2004) observed, HRD in small organizations should not be understood simply as a scaled-down version of HRD in larger ones. The current distribution—48.2% of sample units drawn from large organizations, compared with 8.3% from SMEs—therefore raises questions about the range of circumstances for which published empirical evidence is available.

This is a question about the coverage and boundary conditions of an accumulated evidence base, not a finding that existing HRD theories are invalid outside the sampled settings. It does, however, call for theory-testing research to state explicitly the boundary conditions within which a given theory is expected to hold (Busse et al. 2017; Whetten 1989). In line with arguments that development is multidimensional (Garavan et al. 2015), future theoretical tests could examine whether organizational size, occupational status, employment arrangements, and national institutions act as contextual moderators rather than treating such characteristics only as descriptive controls. The relative scarcity of reports addressing disability (0.9%) and sexual orientation (1.5%) additionally limits what can be inferred from the published descriptions about how these dimensions of experience were considered. The percentages should not be read as proof that participants with these characteristics were absent from the studies.

For practitioners, the immediate implication is to assess the match between the population and setting of a study and the circumstances of intended application (Rousseau 2006). In particular, findings based on managerial and large-organization samples should not be transferred uncritically to blue-collar, small-enterprise, or differently institutionalized settings.

Contextual reporting and the interpretability of findings

Who is studied is only one part of the problem. Readers also need enough information to understand how participants were recruited and what conditions shaped the evidence. Although a sampling method was named in 95.0% of the examined studies, convenience and purposive approaches together accounted for 73.4% of sample units, with convenience sampling especially prevalent in quantitative studies (67.3%). This concentration is not new: Dooley and Lindner (2003) noted similar sampling practices in HRDQ more than two decades ago, and Park et al.'s (2024) review of methodological rigor in HRD research suggests that comparable tendencies persist. In addition, 87.6% of all 338 sample units omitted two or more contextual items in the study's coding framework. These findings should be interpreted separately: declaring a method, choosing a defensible method, and documenting the research context are distinct aspects of methodological transparency.

Nonprobability sampling is not intrinsically inappropriate. Purposive selection, for instance, may be integral to qualitative inquiry, while convenience-based recruitment may be consistent with a clearly specified exploratory aim. The relevant questions concern alignment between sampling strategy and research purpose, explicit acknowledgment of limitations, and the amount of contextual detail necessary

for readers to judge applicability. Likewise, nonreporting does not prove that a characteristic was unknown or ignored by the original investigators. Particularly in small qualitative studies, withholding sensitive demographic or organizational details may be ethically warranted to protect confidentiality.

These findings bear on both conditions distinguished in the Literature Review—representativeness and context. Reporting practices may leave readers unable to judge either the breadth of applicability of a claim or the specificity of the conditions under which it was produced. In this respect, the pattern is not simply an instance of the familiar trade-off between generalizability and contextual realism (McGrath 1981), in which gains on one criterion come at the expense of the other; the published record may fall short of supporting either judgment. Rather than showing that the studies themselves were deficient on both criteria, the findings identify where the published record does not supply sufficient information for these judgments, a distinction that is important for cumulative inquiry across applied social science disciplines.

Implications for research and scholarly publishing

The combined findings support a two-part response. At the research-design level, authors can justify why a particular population and setting are theoretically appropriate while specifying which groups and circumstances remain outside the study's evidentiary reach. Comparative and replication designs could then deliberately examine populations and organizational contexts that are underrepresented in this bounded journal corpus. This need not entail treating demographic or organizational diversity as an end in itself: the rationale should arise from the substantive question and the scope of theoretical claims. For studies involving minority or marginalized groups—such as workers with disabilities or sexual minorities, who were rarely reported in this corpus—the notion of micro-emancipation from critical management studies (Alvesson and Willmott 2012; Duberley and Johnson 2009) offers one way to build such concerns into research design and sampling from the outset.

At the reporting level, editorial guidance can encourage transparent descriptions of recruitment, participant characteristics, organizational features, and relevant cultural or institutional settings. We therefore propose an HRD-oriented reporting checklist; however, a flexible, context-sensitive approach is preferable to imposing identical mandatory variables on all quantitative and qualitative designs. Reporting expectations should reflect analytic relevance, confidentiality, and methodological traditions, drawing on established reporting guidance such as APA JARS where applicable. When information cannot be disclosed, authors can explain the limitation without compromising participant protection.

Finally, the evidence raises a question about how editorial priorities, access to organizations, research funding, and academic evaluation systems shape which subjects and settings enter the published record. Those mechanisms were not measured here and should therefore be examined as hypotheses for future comparative studies, rather than asserted as explanations for the distributions observed.

Limitations and future research

First, the analysis is a census of empirical articles in two AHRD-affiliated journals over 2016–2025, not a census of HRD scholarship globally. Relevant research in other HRD and training journals, HRM and education outlets, and non-English-language publications could exhibit different patterns. The

findings therefore establish the profile of this particular publication corpus rather than the distribution of research participants across the HRD field as a whole. Comparisons across language communities, journals, and publication models would help determine the extent to which these patterns are outlet-specific.

Second, coding was restricted to information available in published reports. Missing information cannot be equated with omission during the original research process; confidentiality requirements, word limits, and disciplinary conventions may account for some instances of nonreporting. Nor can the observed frequencies establish whether individual samples were biased relative to their intended target populations.

Third, the LCA was exploratory and depended on five selected indicators, including both first-author WEIRD status and features of study samples. A different indicator set or class solution might produce a different profile structure. Classification uncertainty and model selection should be acknowledged explicitly; interpretation of the classes should not imply that they reveal exhaustive or inherent types of HRD knowledge production. Finally, the pooled decade-wide analysis does not directly test changes before and after particular events, including the COVID-19 pandemic; future longitudinal comparisons could address these questions.

Concluding Remarks

Building on concerns regarding research subjects in HRD and other applied social sciences, this study established levels of context as an analytic framework and applied it to investigate bias in research subjects and deficits in information about research subjects in the empirical HRD articles published in HRDQ and HRDI. The intent behind this diagnosis was to invite reflection across HRD and neighboring applied fields such as management, organizational psychology, education, and public administration on the reduced diversity of research subjects and potential research decontextualization. Our intention is not to rebuke fellow scholars but to offer a starting point for considering what empirical inquiry in these fields should attend to going forward and what agenda the broader scholarly community might pursue together.

Lastly, we suggest that the recurring patterns of concentration identified in this study—for example, those seen in the Western-Managerial class (Class 1) and the Non-Western Large Corporate-Managerial class (Class 4)—may reflect structural incentives as much as individual choice. Although these mechanisms were not measured here, such concentration may be less a matter of individual researchers' lack of rigor than a structural product of internalized quantified performance metrics and neoliberal modes of university management, including faculty merit review, the pursuit of Social Sciences Citation Index journal and impact factor rankings, and the narrowing of academic specialization (Park et al. 2023). Rather than assuming the role of a scapegoat or victim of the system, we take heed of the view that no self-governing group is better positioned than researchers—university-based researchers, in particular—to lead such change (Alvesson et al. 2017).

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