Advances in Quantitative Evaluation Models for Measuring Corporate Diversity and Inclusion Investments

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Abstract
Corporate expenditure on diversity and inclusion (D&I) grew sharply between 2020 and 2022, yet the evaluation methods used to justify that expenditure lagged well behind it. Most organizations continued to report headcount ratios that describe a workforce state rather than estimate the return generated by an investment. This paper reviews the quantitative evaluation models available as of 2022, traces their development across three methodological generations, and assesses how well each supports causal inference about D&I investments. It examines nine families of technique: utility-analysis and human capital return on investment (ROI) models, quasi-experimental econometric designs, latent-variable psychometrics, stochastic flow models of the talent pipeline, pay equity decomposition, organizational network analysis, causal machine learning, impact-weighted accounting, and real-options framing. The review finds that the principal advance of the 2020 to 2022 period was not a single new estimator but a shift in the unit of analysis, moving from stock measures of representation toward flow, perception, and monetized outcome measures. It also finds that this advance was accompanied by a widening validity gap, in which disclosure mandates and index providers standardized precisely the metrics with the weakest link to firm outcomes. Drawing on more than two hundred studies from adjacent applied literatures, including occupational safety climate, data governance, internal audit, marketing attribution, procurement, health equity, energy justice, condition monitoring, and education, it identifies six transferable methodological commitments that current D&I disclosure frameworks omit. The review then sets out a layered correspondence between evaluation questions, estimators, and identifying assumptions, running from committed input through activity, proximal outcome, and process outcome to terminal value, together with criteria for assessing whether a given metric is fit for the layer at which it is used. It concludes with a research agenda addressing endogeneity, intersectional small-cell problems, cross-jurisdictional data constraints, and metric gaming.

Keywords: *diversity and inclusion; human capital analytics; return on investment; causal inference; ESG measurement; impact-weighted accounts; people analytics; corporate disclosure*

1. Introduction

Between mid-2020 and the end of 2022, large corporations announced diversity and inclusion commitments at a scale without precedent. Pledges directed at racial equity alone were estimated in the tens of billions of dollars, and the chief diversity officer became one of the fastest-growing senior roles in the corporate hierarchy. By 2022, however, the enthusiasm of the pledge cycle had begun to meet a harder question from boards, institutional investors, and finance functions: what, precisely, did the money buy? That question is a measurement question before it is a strategic one. A firm cannot evaluate an investment whose returns it has not defined, cannot define returns it cannot observe, and cannot observe outcomes it has not instrumented. The dominant corporate practice through 2022 was to answer with representation statistics, typically the share of women in the workforce, the share of underrepresented ethnic groups in management, and the composition of the board. These are useful descriptive facts. They are not evaluations. They describe the state of a stock at a point in time, say nothing about the flows that produced it, attribute no portion of the change to any specific intervention, and carry no unit of value that a capital allocator can compare against alternative uses of the same funds. The gap between what firms spent and what firms could demonstrate created demand for better models. That demand was met, unevenly, from several directions at once. Labor and financial economists brought quasi-experimental designs built around board quotas and disclosure mandates. Organizational psychologists brought validated inclusion scales and measurement invariance testing. People analytics functions inside firms brought stochastic pipeline models and organizational network analysis. Accounting researchers brought monetization frameworks that expressed workforce outcomes in currency units. Rating agencies and index providers brought composite scores that were widely adopted precisely because they were easy to compute, and widely criticized for the same reason.

This paper reviews that landscape as it stood in 2022. It is a methodological review rather than an empirical study, and it pursues two aims: to establish what each available family of estimators can and cannot identify, and to set out the identifying assumptions on which any resulting claim about return depends. The review draws deliberately on applied literatures outside the diversity field, since the attribution problem that D&I evaluation faces is a general one and has been formalized more completely elsewhere.

2. Conceptual background

2.1 Diversity, inclusion, and equity as distinct constructs

A recurring source of measurement error is the treatment of diversity and inclusion as a single latent construct. They are not. Diversity is a property of a collective, describing the distribution of attributes across its members. Inclusion is a property of individual experience within that collective, describing the degree to which a person is treated as an insider while retaining distinctiveness. Equity is a property of the organizational process, describing whether allocation of pay, promotion, assignment, and exit is conditionally independent of protected characteristics.

These three properties require different measurement instruments and admit different estimators. Diversity is measured by dispersion indices applied to administrative records. Inclusion is measured by validated psychometric scales applied to individuals. Equity is measured by conditional statistical tests applied to allocation decisions. Collapsing them into a single score, as most composite indices did through 2022, guarantees that the resulting number cannot be interpreted. A widely used taxonomy makes this precise, distinguishing diversity as separation (differences in position along a continuum), variety (differences in kind), and disparity (differences in concentration of a valued resource). The distinction matters because each type predicts different

group outcomes and requires a different index. Variety is appropriately captured by Blau's index or entropy measures. Disparity requires concentration measures such as the Gini coefficient or coefficient of variation. Applying a variety index to a disparity construct, a common error, produces a number that moves in the wrong direction relative to the phenomenon of interest.

2.2 Investments and states as objects of evaluation

The second framing point concerns the object of measurement. A D&I *investment* is a bundle of resources committed to changing an organizational process. Its evaluation requires an estimate of the change in outcomes attributable to that commitment, net of what would have occurred anyway. This is a counterfactual quantity. Representation levels are not counterfactual quantities, and observed changes in representation confound intervention effects with labor market supply shifts, macroeconomic turnover cycles, acquisition activity, and secular demographic change in the applicant pool. The literature evaluating whether particular interventions work has generally been more sobering than the corporate business case literature. Analyses of three decades of federal EEO-1 filings across more than seven hundred establishments have found that structures assigning explicit responsibility for change, such as diversity committees and dedicated staff, predict subsequent gains in managerial diversity, whereas diversity training and evaluation programs do not, and sometimes predict declines. A large field experiment on online diversity training at a multinational found effects on attitudes that were small, concentrated among groups already sympathetic, and largely absent in behavior. These findings do not establish that D&I investment is unproductive. They establish that the modal intervention through the 2010s had not been shown to be productive, and that evaluation designs strong enough to detect the difference were rare.

2.3 The financial-performance evidence

The widely circulated correlational business case, most visibly a series of consultancy studies published through 2020, reports that firms in the top quartile of executive gender and ethnic diversity outperform those in the bottom quartile on profitability. This finding is cross-sectional and does not identify a causal effect. Firms that are profitable can afford to recruit widely, invest in employer brand, and locate in diverse labor markets, all of which generate the observed association without any causal path from diversity to profit.

The causal literature is considerably less supportive. Studies exploiting Norway's mandated forty percent female board quota report significant negative announcement and valuation effects, attributed to constrained director selection rather than to gender. The same quota has been associated with fewer workforce reductions and lower short-term profits, and with improvement in the observable characteristics of women on boards but little detectable spillover to women lower in the corporate hierarchy. Negative announcement returns have been documented around California's SB 826, and commentators have argued from this body of evidence that mandated board diversity rules are unlikely to benefit investors. Research on voluntary variation rather than mandates finds that gender-diverse boards monitor more intensively, with effects on firm value that are positive in weakly governed firms and negative in well governed ones.

The interpretive point is that weak financial evidence does not invalidate D&I investment. It relocates the justification. If the return is primarily social, distributive, or risk-mitigating rather than directly profit-generating, then the evaluation model must be built to measure those returns rather than to search for a profit effect that theory does not strongly predict. Much of the methodological advance discussed below follows from taking this relocation seriously.

3. The development of measurement practice

The models in use by 2022 can be organized into three overlapping generations, summarized in Table 1.

Table 1. Generations of D&I measurement practice

Generation	Period of dominance	Unit of analysis	Representative instruments	Principal limitation
First: representation counting	1970s to mid-2000s	Stock of headcount by category	EEO-1 category counts, Blau index, Shannon entropy, Herfindahl-Hirschman index	Describes state, not process or effect; silent on inclusion and equity
Second: composite scoring and rating	mid-2000s to early 2020s	Firm-level aggregate score	Refinitiv D&I Index, Bloomberg Gender-Equality Index, S&P Global CSA, JUST Capital rankings, GRI 405, SASB human capital topics, WEF Stakeholder Capitalism Metrics	Opaque weighting, disclosure-driven bias, low convergent validity across providers, gameable
Third: causal, latent, and monetized	approximately 2018 to 2022 and continuing	Individual transitions, perceptions, and monetized outcomes	Quasi-experimental designs, item response theory scales, Markov pipeline models, Oaxaca-Blinder decomposition, impact-weighted accounts, causal machine learning	Data-intensive, sensitive to identification assumptions, difficult to standardize across firms

3.1 Dispersion indices

The first generation applied dispersion statistics from ecology and sociology to workforce categories. Blau's index of heterogeneity,

$$B = 1 - \sum_{i=1}^{k} p_i^2$$

where p_i is the proportion of the workforce in category i, remains the most common. Teachman's entropy index,

$$H = -\sum_{i=1}^{k} p_i \ln p_i$$

is more sensitive to small categories and therefore better suited to detecting the presence of very small groups, which matters for intersectional analysis.

Both indices share three structural weaknesses. They are insensitive to hierarchical position, so a firm with proportional representation concentrated entirely in junior grades scores identically to one with representation distributed across grades. They are silent on process, since two firms with the same index value may have reached it through entirely different hiring and attrition dynamics

with entirely different sustainability. And they treat categories as exhaustive and mutually exclusive, which fails for multiracial identity, non-binary gender, disability, and any intersectional cell.

3.2 Composite indices and disclosure frameworks

The second generation aggregated heterogeneous indicators into single scores. By 2022 the principal instruments included the Refinitiv Diversity and Inclusion Index, the Bloomberg Gender-Equality Index, the S&P Global Corporate Sustainability Assessment, and the JUST Capital rankings, alongside disclosure frameworks including GRI 405 on diversity and equal opportunity, the SASB human capital standards, and the World Economic Forum Stakeholder Capitalism Metrics released in 2020. Composite indices solved a real coordination problem. They gave investors a comparable number where none existed. But they introduced three systematic distortions. First, weighting is generally undisclosed or arbitrary, so the score has no interpretable unit and small methodology changes move rankings substantially. Second, they reward disclosure rather than performance, since a firm that publishes more data scores higher on many providers' schemes than an equally diverse firm that publishes less, biasing scores toward large firms in permissive jurisdictions. Third, convergent validity across providers is weak, mirroring the well-documented divergence among ESG ratings more broadly, which means the choice of provider substantially determines the conclusion.

3.3 Causal, latent, and monetized approaches

The third generation, which is the subject of Section 4, abandoned the goal of a single comparable score in favor of estimator-specific answers to specific questions. Its defining move was the shift in unit of analysis away from the firm-year stock toward the individual transition, the individual perception, and the monetized outcome. The most influential single demonstration of the perception approach in this period drew on large-scale employee survey data through 2021 to construct a DEI measure from thirteen employee-perception items. That measure correlated only weakly with board, senior management, and workforce demographic diversity, and it was the perception measure, not the demographic measure, that was associated with future accounting performance and earnings surprises. The finding is important for evaluation design because it implies that the metric almost universally reported by firms and required by regulators is not the metric that predicts outcomes.

4. Model families and their identification properties

4.1 Utility analysis and human capital return on investment

The oldest formal apparatus for valuing a human capital intervention is utility analysis, descending from the Brogden-Cronbach-Gleser model and developed subsequently for practitioner use in the human capital accounting literature. In its standard form, the expected utility of a selection or development intervention is

$$\Delta U = N \cdot T \cdot r_{xy} \cdot SD_y \cdot \bar{Z}_x - C$$

where N is the number of people affected, T the expected duration of the effect, r_{xy} the validity coefficient linking the intervention to performance, SD_y the standard deviation of job performance in monetary units, $\bar{Z}_x$ the standardized mean gain, and C the total cost.

Applied to D&I, the model is most defensible when used for cost-avoidance rather than value-creation claims. The clearest application is turnover. If an inclusion intervention reduces the regretted attrition hazard for a defined population, and the fully loaded replacement cost of a departure in that population is estimable from separation, recruitment, onboarding, and productivity ramp costs, then the avoided cost is a legitimate and auditable return component.

The parallel practitioner framework is the Phillips return on investment methodology, a five-level chain running from reaction, to learning, to application, to business impact, to ROI expressed as

$$\text{ROI \%} = \frac{\text{Net program benefits}}{\text{Program costs}} \times 100$$

Its central methodological weakness in D&I application is the isolation step. Phillips' framework isolates program effects using expert estimation, participant attribution, or trend-line extrapolation. None of these is a credible identification strategy for an intervention deployed simultaneously across an organization during a period of unusual labor market volatility. Reported D&I ROI figures derived this way, including the frequently cited case results in the range of one hundred to two hundred percent, should be read as internally consistent accounting exercises rather than as causal estimates.

Utility analysis therefore identifies a monetized benefit conditional on an assumed effect size. It does not identify the effect size itself, which must come from elsewhere.

4.2 Quasi-experimental econometric designs

The strongest identification available for D&I evaluation comes from designs that exploit variation the firm did not choose. Four are relevant.

Difference-in-differences. Where an intervention is rolled out to some business units before others, the staggered adoption supports a DiD estimator:

$$Y_{it} = \alpha_i + \lambda_t + \beta D_{it} + X_{it}'\gamma + \varepsilon_{it}$$

with unit fixed effects α_i, period fixed effects λ_t, and treatment indicator D_{it}. The parallel trends assumption is the binding constraint. It is frequently violated in D&I rollouts because firms pilot in units with the most favorable conditions or the most acute problems, either of which breaks the assumption. Researchers working in this period increasingly adopted the staggered-adoption estimators developed in the econometrics literature during this period, which correct the negative-weighting bias that two-way fixed effects estimators exhibit when treatment timing varies and effects are heterogeneous. This correction is directly relevant to phased D&I rollouts and was underused in applied corporate work through 2022.

Regulatory discontinuities. Threshold-based mandates create regression discontinuity opportunities. The UK gender pay gap reporting regulations, effective 2017, apply to employers with 250 or more employees, creating a sharp cutoff. Similar thresholds exist in EU member state reporting rules. Firms just above and just below the threshold are plausibly comparable, allowing estimation of the effect of mandated transparency on subsequent pay gaps and composition.

Mandate-based natural experiments. Board quotas and listing standards supply exogenous variation in composition. The Norwegian quota literature cited in Section 2.3 is the canonical example. The Nasdaq board diversity rules, approved by the SEC in August 2021, required listed companies to publish a standardized board diversity matrix by the later of August 2022 or the filing of their 2022 proxy statement, with the comply-or-explain objective provisions scheduled to phase in thereafter. This creates a well-dated, cross-sectionally comparable disclosure shock available as an identification source, though the rules face active legal challenge whose resolution would itself

constitute a second event window. California's SB 826 and AB 979 were struck down in state court in 2022, providing further variation.

Instrumental variables. Valid instruments for firm-level diversity are scarce. Local labor market demographic composition, interacted with a firm's pre-existing establishment footprint in a shift-share design, is the most commonly attempted. The exclusion restriction is fragile, because local demography plausibly affects firm outcomes through customer base and cost structure independent of workforce composition.

These designs identify the causal effect of a specific, externally imposed change. They do not identify the effect of the voluntary, bundled, internally designed interventions that constitute most corporate D&I spending.

4.3 Latent variable and psychometric models

Inclusion is unobservable and must be inferred from responses to items. The measurement literature accordingly treats it as a latent construct requiring formal psychometric validation.

Established instruments include the inclusion-exclusion scale developed in the late 1990s, a perceived group inclusion scale that separates belongingness from authenticity, and a more recently validated workgroup inclusion scale. Research on climate for inclusion, a construct distinct from diversity itself, has established that it moderates whether gender-diverse groups experience relationship conflict, which is exactly the kind of conditional relationship that a single composite score cannot represent.

Three psychometric procedures are essential and were routinely omitted in corporate practice through 2022.

Confirmatory factor analysis tests whether the assumed factor structure fits the data, rather than assuming that items grouped under a heading measure one thing.

Measurement invariance testing determines whether the instrument means the same thing across the groups being compared. This is the critical omission. Comparing mean inclusion scores across racial or gender groups is uninterpretable unless configural, metric, and scalar invariance have been established. If groups interpret an item differently, an observed mean difference may reflect differential item functioning rather than differential experience, and the resulting intervention will be aimed at the wrong target.

Item response theory models the probability of a given response as a function of the respondent's latent position and the item's difficulty and discrimination parameters. In the two-parameter logistic form,

$$P(X_{ij} = 1 \mid \theta_j) = \frac{1}{1 + e^{-a_i(\theta_j - b_i)}}$$

IRT permits construction of shorter instruments with equivalent precision, supports computerized adaptive testing, and places respondents on a common scale even when different items are administered. This last property makes longitudinal comparison possible when survey content changes, which it always does.

Psychometric models identify the level and distribution of a validated latent experience, comparably across groups and over time. They identify no causal effect, and they speak to perception rather than to behavior.

4.4 Stochastic flow models of the talent pipeline

The most consequential reframing of the 2018 to 2022 period was the treatment of workforce composition as the equilibrium of a flow system rather than as a state to be targeted directly. This

follows the tradition of stochastic modelling of social processes and connects to the tournament mobility literature on career patterns within firms.

Model the workforce as a set of grades $1, \dots, k$ with a transition matrix P whose entry p_{ij} is the probability that a member of grade i moves to grade j in one period, augmented by exit probabilities and an external hiring vector. The composition vector evolves as

$$n_{t+1} = n_t P + h_t$$

Estimating P separately by demographic group is the analytical core. The resulting comparison isolates precisely where a group's trajectory diverges: at entry, at first promotion, at the transition into people management, or at exit. This is actionable in a way that an aggregate representation percentage never is.

Three refinements matter. First, *survival and hazard modeling* of attrition, typically via Cox proportional hazards, allows estimation of group differences in exit risk conditional on tenure, grade, performance rating, manager, and compensation. Second, *steady-state projection* answers the question boards actually ask, which is whether current flow rates can reach a stated composition target, and by when. In many documented cases the answer is that they cannot at any feasible hiring rate, because the binding constraint is a mid-career promotion or attrition differential rather than the entry pipeline. Third, *decomposition of change* attributes an observed shift in composition to its component flows, separating hiring, promotion, and attrition contributions, which prevents a firm from claiming credit for a representation gain that was in fact produced by disproportionate junior hiring masking senior attrition.

The mechanism literature supports the emphasis on transitions. The opportunity structure for discrimination has been shown to concentrate in discretionary allocation decisions rather than in formal hiring gates. Performance-reward linkages have been documented to differ by group even where performance ratings do not, and explicitly meritocratic organizational cultures have been shown to increase biased allocation rather than to reduce it. These findings imply that promotion and reward transitions, not headcount, are where measurement effort should concentrate.

Flow models identify the specific process locations at which group trajectories diverge, and the feasibility of composition targets under current dynamics. They do not identify why the divergence occurs, or whether it is discriminatory.

4.5 Pay equity decomposition

Pay equity analysis is the most methodologically mature area of D&I measurement, because it has been shaped by decades of litigation and regulatory scrutiny that impose evidentiary standards.

The essential distinction is between the *unadjusted* gap, which compares raw mean or median pay across groups, and the *adjusted* gap, which compares pay conditional on legitimate compensable factors. The two answer different questions. The unadjusted gap measures the aggregate distributional outcome, including occupational segregation and grade distribution, and is the quantity that UK and EU reporting regimes require. The adjusted gap estimates whether like is paid like within comparable roles, and is the quantity relevant to equal pay liability. Reporting only the adjusted gap conceals segregation. Reporting only the unadjusted gap conflates segregation with within-role discrimination. Rigorous practice reports both.

The Oaxaca-Blinder decomposition separates the raw differential into an explained component attributable to differences in observed characteristics and an unexplained residual:

$$\bar{Y}_A - \bar{Y}_B = (\bar{X}_A - \bar{X}_B)'\hat{\beta}_B + \bar{X}_A'(\hat{\beta}_A - \hat{\beta}_B)$$

The first term is the endowment effect, the second the coefficient effect. Two interpretive cautions apply. The unexplained residual is not an estimate of discrimination; it is an estimate of everything

not in the model, including unobserved productivity and any omitted legitimate factor. And conditioning on a variable that is itself the product of biased allocation, most obviously job grade or prior salary, mechanically absorbs discrimination into the explained component. The choice of controls is therefore a substantive claim about the causal structure, not a technical detail.

Quantile regression extensions locate the gap in the distribution, distinguishing sticky floors from glass ceilings. This distinction has direct intervention implications, since the two call for entirely different remedies. The regulatory trajectory in the focal period reinforced this family of models. The UK regime had operated since 2017. The EU Pay Transparency Directive, proposed in March 2021, reached provisional political agreement in December 2022, extending obligations to individual pay information rights and joint pay assessments where unjustified gaps exceed a threshold. The Corporate Sustainability Reporting Directive, Directive (EU) 2022/2464, was adopted in November 2022, with the associated European Sustainability Reporting Standards specifying own-workforce disclosures including gender pay gap and pay ratio metrics under assurance requirements. Assurance is the material change: a metric subject to external assurance must be reproducible from auditable source systems, which forecloses the definitional discretion that made voluntary D&I disclosure incomparable.

Decomposition methods identify conditional pay differentials, separated into structural and within-role components. They do not identify discrimination without additional assumptions about the completeness of the control set.

4.6 Organizational network analysis

Organizational network analysis measures inclusion behaviorally rather than by self-report, using the structure of interaction. Data sources include collaboration platform metadata, calendar and meeting records, and survey-elicited advice and support ties.

The relevant metrics are structural. Degree centrality measures the volume of connection. Betweenness centrality measures brokerage position, the extent to which a person bridges otherwise disconnected parts of the organization. Constraint, in Burt's formulation, measures the redundancy of a person's contacts. E-I index measures the ratio of external to internal ties for a defined group, and is a direct operationalization of network segregation.

Applied to D&I, ONA can detect patterns that neither headcount nor survey data reveal: that members of an underrepresented group are structurally peripheral despite proportional representation, that they hold fewer ties to senior decision-makers, or that mentorship and sponsorship networks are homophilous. It has been argued that relational data of this kind constitutes the substantive content of people analytics, as distinct from the descriptive dashboards that dominated practice. Three constraints are serious. Privacy and consent obligations under GDPR and comparable regimes require careful legal basis, aggregation thresholds, and transparency to employees. Passive collection risks perceived surveillance, which can itself degrade the inclusion it purports to measure. And network structure is endogenous to role, tenure, and location, so raw group differences in centrality require conditioning before they support any inference. Network analysis identifies structural marginalization that is not visible in composition or perception data. It does not identify intent, causality, or whether the observed structure is consequential for outcomes, absent linkage to promotion and retention records.

4.7 Machine learning and causal machine learning

Two distinct applications should not be confused.

Predictive machine learning forecasts outcomes such as attrition risk or promotion likelihood. It is useful for targeting, identifying which populations warrant intervention. It is not useful for evaluation, because a predictive model optimized for accuracy will encode existing patterns, including discriminatory ones, and its coefficients carry no causal interpretation. Deploying a predictive model trained on historical promotion outcomes to guide future promotion recommendations reproduces the disparities the D&I programme exists to remove.

Causal machine learning is the relevant advance. Double or debiased machine learning uses flexible learners to estimate nuisance functions, the outcome model and the treatment propensity, while preserving valid inference on the treatment parameter through Neyman-orthogonal scores and cross-fitting. In a partially linear specification,

$$Y = \theta D + g(X) + U$$
$$D = m(X) + V$$

the target θ is estimated after partialling out high-dimensional confounders X using machine learning for g and m. This is well suited to D&I evaluation, where the confounder set is large, includes rich text and behavioral features, and has an unknown functional form. Causal forests extend this to heterogeneous treatment effects, estimating how the effect of an intervention varies across subgroups, which is directly relevant given that D&I interventions are widely expected to have heterogeneous and occasionally negative effects across populations.

Uplift modeling, which estimates the incremental effect of treatment at the individual level rather than the outcome level, supports the resource allocation question of which employees or units to treat. Natural language processing constitutes a further application, applied to job advertisements for gendered wording, to performance review text for the documented pattern in which women receive more communal and less agentic feedback, and to employee free-text and public review data. The last of these was illustrated during the focal period by text analysis of employee reviews used to construct culture measures, including treatment of diversity, which identified toxic culture as a far stronger predictor of attrition during the 2021 turnover surge than compensation.

Causal machine learning identifies treatment effects under high-dimensional confounding, together with effect heterogeneity across subgroups. It identifies nothing at all if the unconfoundedness assumption fails, since flexible estimation does not repair a missing counterfactual.

4.8 Impact-weighted accounting and monetization

The impact-weighted accounts research programme, developed in the accounting literature from 2019 onward, attempts to express workforce outcomes in monetary units so that they can enter financial statements alongside conventional line items. Employment impact accounting monetizes dimensions including wage quality relative to a living wage benchmark, career advancement, opportunity and diversity relative to a local labor market benchmark, health and wellbeing, and community effects such as the labor income multiplier of job creation.

The diversity component is constructed as a comparison of a firm's demographic composition, by wage level, against the composition of the labor market from which it draws, monetized through the wage differential that the deviation implies. This construction has two attractive properties for evaluation. It benchmarks against an external and defensible reference rather than an arbitrary target, and it produces a currency-denominated figure that finance functions and capital allocators can compare against alternative uses of funds.

The limitations are equally clear. Monetization requires shadow prices that are contestable, and small changes to the benchmark or discount rate move the result substantially. Attribution to firm action rather than to the composition of the local labor market is difficult. Reliance on public disclosure limits coverage, particularly in jurisdictions where demographic data collection is restricted. And expressing an equity outcome in currency invites the substitution of the monetized proxy for the underlying goal. Impact-weighted accounting identifies a comparable, benchmark-referenced monetary value for workforce composition and quality. It does not identify the marginal effect of any particular investment, since the measure is a level rather than a difference.

4.9 Real options and portfolio framing

A final and less developed family treats D&I investment as a portfolio of options rather than as a set of projects with point-estimate returns. The framing is appropriate because D&I interventions share the characteristics that make real options analysis apt: high uncertainty about payoff, substantial irreversibility in reputational commitment, sequential decision structure, and long, variable lags between expenditure and observable outcome.

Under this framing, a pilot programme is priced as a call option on organizational learning, with value derived from the right to expand if early indicators are favorable and to abandon if they are not. This reframing resolves a practical evaluation problem, which is that a pilot with a negative measured ROI may nonetheless have positive value if it resolved uncertainty cheaply. It also provides an explicit rationale for staged investment and for the small-scale randomized designs that generate the information the option requires.

Portfolio framing addresses a second practical problem. Firms typically fund a bundle of interventions and then attempt to evaluate the bundle. Treating the bundle as a portfolio with distinct risk and return profiles, correlated exposures, and a defined evaluation budget makes explicit the trade-off between funding many small unevaluable interventions and funding fewer interventions at a scale that permits evaluation.

The approach remained largely conceptual as of 2022, with limited empirical application. Its practical value lies less in producing a number than in disciplining the sequencing of investment and evaluation.

5. Adjacent measurement literatures

The estimators reviewed in Section 4 were not developed for diversity and inclusion. They were adapted to it from fields that had already confronted the same underlying problem, which is the attribution of outcomes to investments in organizational systems where the outcome of interest is latent, lagged, unevenly observed, and jointly determined by many causes. That problem is not distinctive to D&I. It recurs wherever an organization spends money on a capability rather than on a product, and the applied literatures that have wrestled with it longest offer transferable apparatus rather than merely rhetorical analogy. This section reviews those adjacent literatures. The organizing logic is methodological rather than topical: each subsection identifies a measurement problem that a neighbouring field has formalized, and states what the formalization contributes to the evaluation of D&I investment. The breadth is deliberate. A field that borrows only from within its own subject boundary tends to reproduce the limitations of its own data, and much of what is weakest in current D&I measurement, particularly the reliance on single-point stock indicators and on post hoc attribution, has been solved elsewhere under a different name.

5.1 Safety climate

Occupational safety management is the nearest structural relative of D&I measurement. Both concern a latent organizational property that is unobservable directly, both are measured through a mixture of administrative records and perception surveys, both suffer acute lagging-indicator problems because the terminal outcome is rare and severe, and both are subject to strong incentives to under-report. The safety literature resolved these problems earlier and more thoroughly, and the resolution is instructive. The central move was the shift from lagging to leading indicators. Counting incidents after they occur is the safety equivalent of counting representation after the pipeline has produced it: accurate, auditable, and almost useless for management, because by the time the number moves the causal window has closed. Work on near-miss and hazard observation systems developed the alternative, treating the volume and quality of proactively reported precursor events as the primary management signal (Arumosoye & Obriki, 2019; Obogo et al., 2021a; Obriki & Arumosoye, 2018). The analytical subtlety is that a rise in reported near misses is ambiguous: it may indicate deteriorating conditions or improving willingness to report. This is precisely the interpretive problem that self-identification disclosure rates present in D&I measurement, discussed in Section 7, and the safety field's answer, which is to model reporting propensity separately from event incidence rather than to treat the raw count as a performance metric, transfers directly. A second contribution is the formalization of causation pathways rather than correlation with outcomes. Conceptual models of human error causation in high-risk work locate failure in the interaction of task design, supervision, fatigue, and organizational pressure rather than in individual carelessness (Obriki & Arumosoye, 2020; Obriki & Arumosoye, 2022; Obogo et al., 2020b). Applied to inclusion, the parallel claim is that exclusionary outcomes are produced by allocation processes and decision architecture rather than by individual attitude, which is consistent with the finding that attitude-focused training produces little behavioral change. Work on leadership-driven culture transformation and on the frequency of management walkthroughs as a predictor of downstream safety performance provides an operational measure of leader behavior that has no established D&I equivalent (Obogo et al., 2019a; Obriki & Arumosoye, 2019). The frequency and quality of senior leader engagement in inclusion processes is measurable in exactly the same way and is rarely measured at all. Third, the safety literature developed maturity models that stage organizational capability rather than scoring it on a single scale, which addresses the composite index problem identified in Section 3.2. Organizational learning-based maturity models treat continuous improvement capability as the object of assessment (Arumosoye & Obriki, 2021), while governance-oriented models separate the accountability structure from the outcomes it produces (Arumosoye & Obriki, 2020; Obogo et al., 2022; Obogo et al., 2019b). This separation matters for D&I because the strongest available evidence on intervention efficacy concerns accountability structures specifically, and a maturity model measures structure directly rather than inferring it from outcomes.

Fourth, contractor and extended-workforce measurement is well developed in safety and almost absent in D&I. Contractor safety performance frameworks address the problem that the entity accountable for outcomes does not employ the people exposed to risk (Obogo et al., 2021c; Obogo et al., 2019c; Obogo et al., 2020c). The D&I analogue is the contingent, agency, and outsourced workforce, which is systematically excluded from corporate diversity reporting even where it constitutes a substantial share of the people doing the work, and whose exclusion mechanically inflates reported composition when outsourced functions are demographically distinct from the direct workforce.

Finally, the safety field treats training as a component of a control system rather than as an intervention in itself, with fidelity and dosage tracked as separate variables (Obriki et al., 2022a; Obogo et al., 2020a), and it maintains explicit models for the rare high-consequence event, including emergency preparedness and evacuation performance (Obriki et al., 2022b), lifting and rigging risk pathways (Arumosoye & Obriki, 2022; Obogo et al., 2020b), heat stress exposure (Arumosoye & Obriki, 2018), incident prevention modelling (Obogo et al., 2021b), and the institutionalization of practices so that they survive personnel turnover (Obriki & Arumosoye, 2021). The last of these is the most underdeveloped idea in D&I practice. Institutionalization, meaning the degree to which a practice persists when its sponsor departs, is measurable through practice-persistence rates and is a better indicator of durable change than any composition figure.

5.2 Data governance, privacy, and the legal envelope of demographic measurement

Every D&I metric is constrained by what may lawfully be collected, stored, processed, and disclosed. This constraint is treated in most D&I writing as a footnote and in the data governance literature as the primary design problem, which is the correct ordering.

Comparative analysis of data protection regimes establishes that demographic attributes fall into the most heavily restricted category in most modern frameworks, requiring a specific lawful basis rather than general consent, and that the restrictions differ materially across jurisdictions in ways that defeat naive global aggregation (Mbonu et al., 2019a; Annan, 2022). The practical consequence for a multinational is that a single global diversity figure is not merely difficult to compute but, in some configurations, unlawful to compute, and the frameworks for legal and ethical handling of personal data developed in this literature supply the governance apparatus that D&I programmes generally lack (Mbonu et al., 2018). Data protection impact assessment is the specific instrument of interest. It requires an ex ante analysis of processing purpose, necessity, proportionality, and residual risk before a new data flow is created (Mbonu et al., 2022a). Applied to D&I analytics, particularly to the organizational network analysis discussed in Section 4.6 and to any passive behavioral collection, this instrument converts a diffuse privacy concern into a documented decision with an owner. Its adoption would materially improve the defensibility of people analytics programmes, which frequently proceed on the assumption that internal data is unproblematic because it is already held. Identity and access management determines who inside the organization can see demographic data at individual granularity, and it is the operational control that makes small-cell analysis possible without re-identification exposure (Mbonu et al., 2020c; Mbonu et al., 2022b). Related work on risk-based business continuity and on infrastructure-as-code governance addresses the reproducibility question that assurance requires, since a metric computed by an analyst on a laptop is not auditable in the sense the CSRD contemplates (Mbonu et al., 2021a; Mbonu et al., 2020b). Enterprise log analytics and automated monitoring provide the audit trail that demonstrates who accessed sensitive workforce data and when (Mbonu et al., 2019b), and forensic analytics methods extend the same logic to communications data (Mbonu et al., 2021c). The literature on artificial intelligence in security and governance contexts contributes a further caution. Machine learning applied to sensitive personal data introduces failure modes that are not present in conventional analysis, including inference of protected attributes that were never collected, model inversion, and adversarial manipulation (Mbonu et al., 2021b; Mbonu et al., 2022c; Borah et al., 2022). A D&I analytics programme that avoids collecting ethnicity but deploys a model whose features permit its reconstruction has not avoided the legal or ethical exposure. Privacy-preserving data architectures for regulated industries offer the constructive response, holding sensitive attributes in a governed enclave and exposing only aggregate statistics to

analytical consumers (Atakpa & Abolaji, 2022). Agile supply chain data governance work extends the same architecture to third-party data flows (Mbonu et al., 2020a), which is directly relevant to supplier diversity measurement discussed in Section 5.7.

5.3 Audit, assurance, and internal control

The most consequential regulatory development described in Section 4.5 was the extension of assurance to workforce metrics. Assurance is an audit concept, and the internal audit literature specifies what a metric must satisfy to be assurable.

Risk-based internal control models establish the basic architecture, in which control activities are allocated according to assessed risk rather than uniformly, and in which the design of the control is documented separately from its operating effectiveness (Akomolafe & Agu, 2019a; Akomolafe & Agu, 2018). Applied to D&I, this distinction separates two questions that practitioners routinely conflate: whether the firm has a pay equity review process, and whether that process operates as designed. A disclosure that reports the former while implying the latter is precisely the kind of claim that assurance is designed to test. Data-driven risk evaluation models for financial institutions in emerging markets contribute the observation that control quality degrades where data quality is weakest, which is a systematic rather than random pattern (Akomolafe & Agu, 2019b). The D&I parallel is exact: demographic data quality is lowest in the jurisdictions and employment categories where inequity risk is highest, so measurement precision and substantive risk are inversely correlated. Work on integrated governance and compliance as a route to financial resilience makes the further point that fragmented control ownership is itself a risk factor (Akomolafe & Agu, 2019c), which bears on the common arrangement in which D&I metrics are owned by human resources, reported by corporate affairs, and assured by no one.

Public sector accounting research contributes the budget compliance perspective, in which the question is not whether an outcome improved but whether funds were spent as authorized and reported as spent (Dogbatsey & Ebhojie, 2018). This is the Layer 1 question in the framework of Section 8, and it is the layer most often skipped. Reconciliation control and financial workflow redesign work formalizes the tracing of a committed amount through to its ultimate application (Dogbatsey et al., 2019), and cross-border segregation of duties addresses the multinational case in which authorization and execution occur in different legal entities (Dogbatsey et al., 2021). A D&I programme that cannot reconcile its stated commitment to its actual disbursement cannot support any return calculation, and pledge-tracking analyses in the 2020 to 2022 period repeatedly found this reconciliation absent. Fraud and forensic analytics contribute the adversarial perspective that metric design requires. Predictive models for anti-money laundering detection are built on the assumption that the measured party is actively optimizing against the measure (Atakpa, 2021), and machine learning approaches to fraud detection formalize the resulting arms race (Atakpa & Abetoh, 2022). Financial forensics techniques address detection after the fact (Ekechi et al., 2022). This literature supplies the analytical vocabulary for the gaming problem set out in Section 6: a metric should be assessed not only on whether it measures the construct but on how it behaves when a rational agent optimizes for it. Work on the relationship between control investment and organizational outcome, including systematic assessment of cybersecurity investment returns, models the same evaluation problem this paper addresses in a domain where the counterfactual is equally unobservable (Ozowara et al., 2022). Comprehensive financial reporting models for compliance strengthening close the loop by specifying the disclosure architecture that assured metrics require (Medon & Oduleye, 2022).

5.4 Attribution modelling in marketing analytics

Marketing analytics has confronted the attribution problem more directly than any other applied field, because marketing spend is large, continuous, multi-channel, and evaluated by finance functions that demand a return figure. The parallel to D&I investment is close enough that the estimators transfer with minimal modification.The core problem is identical. Multiple simultaneous interventions touch an individual over an extended period, the outcome is observed only at the end, and naive attribution assigns the entire effect to whichever touchpoint was last or most easily observed. Systematic treatment of attribution modelling methods catalogues the responses, from rule-based heuristics through to algorithmic and incrementality-based approaches, and documents the bias that each introduces (Sanni et al., 2022b). The finding most relevant here is that last-touch and first-touch heuristics, which are the easiest to compute, are also the most biased, and that the direction of bias is systematic rather than random. The D&I equivalent is the attribution of a promotion outcome to the most recently completed development programme, which is the modal practice in programme evaluation and which shares the bias structure exactly. Analytical models addressing measurement challenges in marketing effectiveness formalize the distinction between measured lift and true incrementality (Sanni et al., 2020a), which is the same distinction as that between an observed change in representation and the change attributable to intervention. Predictive audience segmentation work contributes the heterogeneity insight, namely that an intervention effective in aggregate may be ineffective or counterproductive in identifiable subgroups (Atima et al., 2022), which corresponds directly to the heterogeneous treatment effect estimation discussed in Section 4.7 and to the documented finding that diversity training effects differ sharply by participant group. Business intelligence dashboard frameworks address the executive visibility problem, and the caution they raise is pertinent (Sanni & Atima, 2021b). A dashboard that surfaces the most easily computed metrics tends to entrench them, because visibility creates management attention and management attention creates optimization pressure. Analytics-driven go-to-market frameworks that incorporate compliance and sustainability constraints demonstrate that non-financial objectives can be integrated into a performance measurement system without being reduced to a financial proxy (Sanni & Atima, 2021a), which is the design problem for D&I metrics in a finance-owned reporting environment. Data-driven brand positioning work contributes the reputational measurement dimension (Sanni et al., 2020b), relevant because a substantial part of the claimed return to D&I investment is reputational and is therefore measured, if at all, through instruments developed in marketing. Systematic review of product management strategy contributes the staged decision structure (Sanni et al., 2020c), and adaptive control models contribute the closed-loop formulation in which measurement feeds back into intervention design within the period rather than only at its end (Sanni et al., 2022a). The closed-loop formulation is the practical answer to the lag problem identified in Section 7.

5.5 Financial analytics and the capital allocation frame

If D&I expenditure is to be evaluated as investment, it must eventually be expressed in terms that a capital allocation process recognizes. The corporate financial analytics literature specifies those terms. Conceptual decision models for capital allocation using financial analytics establish the basic requirement, which is that competing uses of funds be expressed in a common unit with a stated time horizon and a stated risk profile (Lawal & Oduleye, 2021a). D&I proposals typically fail this test not because the return is absent but because it is expressed in a unit the allocation process cannot compare. Work on aligning financial planning analytics with corporate strategy addresses the bridging problem, in which strategic priorities that resist quantification must

nonetheless enter a quantified planning process (Lawal & Oduleye, 2021b), and enterprise value creation models supply the linkage from operational metric to valuation (Lawal & Oduleye, 2018a). Data-driven executive decision systems contribute the observation that the binding constraint is usually decision latency rather than analytical sophistication (Lawal & Oduleye, 2019b). A D&I metric produced annually cannot inform a quarterly resource decision regardless of its validity, which argues for the higher-frequency process metrics described in Section 8 rather than the annual composition disclosure. Transfer pricing risk assessment and cross-border tax governance work contributes the multi-entity perspective (Lawal & Oduleye, 2019a; Lawal & Oduleye, 2018b), relevant because workforce metrics in a multinational are produced by legal entities with different data regimes and consolidated by a parent that must attest to the result.

Treasury and strategic finance research extend this to the operating level. Multinational cash flow consolidation and foreign exchange risk work formalizes the consolidation of heterogeneous local measures into a group figure with explicit treatment of the translation assumptions (Dada et al., 2021a), which is the exact structural problem of consolidating jurisdictionally incompatible demographic data. Chief financial officer-led strategic finance models in joint venture contexts address governance where control is shared (Isiekwu et al., 2021), which bears on D&I accountability in joint ventures and franchise structures. Customer relationship management-based forecasting work contributes the pipeline projection apparatus (Dada et al., 2021b), structurally identical to the talent pipeline projection of Section 4.4. Smart contract automation in cross-border payment systems illustrates the more general point that verifiability can be engineered into a process rather than assessed after it (Akomolafe et al., 2022), which is the direction assurance requirements are pushing workforce reporting.

5.6 Predictive analytics, forecasting, and the targeting-evaluation distinction

Section 4.7 distinguished predictive from causal machine learning. The applied forecasting literature makes the same distinction operationally and shows what each is good for.

Advances in demand forecasting demonstrate that flexible learners substantially outperform classical methods on predictive accuracy while offering no causal interpretation of their inputs (Tonoyan et al., 2021a). Predictive cash flow modelling makes the same point in a financial context (Tonoyan et al., 2021b), and algorithmic process optimization work shows how accurate prediction supports resource allocation without any claim about mechanism (Tonoyan et al., 2022b; Tonoyan et al., 2022c). This is exactly the correct posture for attrition-risk modelling in D&I: use the model to decide where to look and where to intervene, and use a different apparatus entirely to decide whether the intervention worked. Geospatial predictive analytics contributes the spatial dimension (Tonoyan et al., 2022a), directly relevant to the shift-share instruments discussed in Section 4.2 and to labour market benchmarking in impact-weighted accounts, where the availability comparison must be constructed from the actual geography of a firm's establishments rather than from a national aggregate. Audience segmentation and forecasting work extends the same methods to population subgroups (Basnet et al., 2021), and resilient logistics frameworks for humanitarian supply chains demonstrate forecasting under conditions of poor data quality and high stakes (Anene & Clement, 2022), which describes the intersectional small-cell problem well.

The most important contribution is the human-in-the-loop literature, which specifies how automated inference and human judgment should be combined when the decision affects people (Ladapo et al., 2022a). The relevant design principle is that the model proposes and the human disposes, with the human's override recorded and analyzed. In a D&I context this is not merely an

ethical safeguard: the record of overrides is itself a dataset revealing where human judgment systematically departs from the model, and its analysis is a direct measurement of decision bias.

5.7 Supplier diversity and procurement as an external investment channel

Supplier diversity is the largest D&I investment channel that receives the least measurement attention. Spend directed to diverse-owned suppliers is straightforward to record, is material in magnitude, and produces effects outside the firm boundary that are entirely absent from workforce composition metrics. The procurement literature supplies the measurement apparatus that supplier diversity programmes generally lack. Strategic procurement optimization frameworks establish the basic structure of category strategy, sourcing decision, and performance management (Okonkwo et al., 2018a; Akinleye & Adeyoyin, 2022b), within which a diversity objective is a constraint or a weighted criterion rather than a separate programme. This framing matters because supplier diversity managed as a separate initiative is structurally vulnerable to being overridden by the cost objective in the main process. Data-driven vendor evaluation models make the trade-off explicit by scoring suppliers on multiple weighted criteria simultaneously (Ahiaeke Patrick et al., 2021), which is the mechanism by which a diversity criterion can survive contact with a procurement decision. Supply chain risk management models contribute the concentration analysis (Agbabiaka et al., 2019), relevant because diverse-owned suppliers are frequently smaller and the risk assessment that governs their qualification is calibrated to larger firms, producing systematic exclusion at the qualification gate rather than at the award decision. Supply chain resilience frameworks show that supplier base diversification and resilience are complementary rather than competing objectives (Ogunwole et al., 2021), which is the strongest available business case argument for supplier diversity and is rarely made quantitatively. Regulatory-compliant procurement frameworks address the documentation burden that qualification imposes (Okonkwo et al., 2021b), itself a barrier that falls disproportionately on smaller suppliers.

The operational literature contributes measurement of the downstream consequences. Materials requirement and inventory availability models link supplier performance to plant uptime (Okonkwo et al., 2021a; Okonkwo et al., 2018b), demurrage elimination models quantify the cost of supply chain failure (Okonkwo et al., 2020), and cost reduction frameworks formalize the savings attribution problem in a way that parallels the D&I attribution problem closely (Okonkwo et al., 2019). Geographic information system-enabled enterprise resource planning frameworks address the location dimension of supplier development (Ahiaeke Patrick et al., 2020), relevant to local content and community investment obligations that frequently accompany diversity commitments in extractive and infrastructure sectors. Process automation in procurement contributes the transaction-level data that measurement requires (Akinleye & Adeyoyin, 2021), and negotiation optimization models quantify the cost consequence of constraints applied to the supplier set (Akinleye & Adeyoyin, 2022a), which is the honest way to state the trade-off where one exists. Sustainable procurement frameworks integrate social criteria into the sourcing decision directly (Efobi et al., 2022a), data-driven lean supply chain models address the efficiency consequence (Efobi et al., 2022b), and performance management frameworks specify the ongoing measurement (Efobi et al., 2021). Visualization work using standard analytical tools demonstrates that the reporting requirement is not technically demanding (Akin-Oluyomi et al., 2020), which locates the obstacle in governance rather than capability. Decision frameworks reconciling chemical safety with circular economy targets illustrate the general structure of multi-objective sourcing decisions where the objectives are not commensurable (Okojie & Abioye, 2020), which is the situation a diversity criterion creates.

5.8 ESG auditing and sustainable procurement disclosure

The convergence of D&I reporting with environmental, social, and governance disclosure means that D&I metrics increasingly inherit the assurance and audit expectations developed for ESG data generally. Predictive approaches to supply chain and ESG auditing demonstrate the shift from sample-based to population-based testing that data availability permits (Aifuwa et al., 2020), which is directly applicable to pay equity testing where full population analysis is feasible and sampling is not necessary. Real-time risk assessment dashboards illustrate the continuous monitoring model that replaces periodic assessment (Filani et al., 2022), and work on ESG data quality and supplier disclosure addresses the upstream data reliability problem that any social metric spanning the value chain must confront (Ike et al., 2021; Ike et al., 2022). The last point is material for D&I because supplier workforce composition, where it is claimed at all, rests on self-reported data with no assurance and no consistent definition. Sustainable procurement governance work addresses the accountability structure for value chain social objectives (Nnabueze et al., 2021), and programmatic strategy for renewable energy integration in large infrastructure contributes the observation that social and local content objectives in major projects require measurement systems designed at the point of project structuring rather than retrofitted (Yeboah & Ike, 2020). The retrofitting problem is the single most common cause of unmeasurable D&I commitments: the commitment is announced, and only afterward is anyone asked how it will be evidenced.

5.9 Process standardization and lean operations

Inclusion outcomes are produced by processes, and process design is the domain of operations management. The lean literature contributes the specific insight that variability and discretion in a process are the principal sources of inconsistent outcomes, which is the operational statement of the bias mechanism located in discretionary allocation decisions.

Standard operating procedures treated as strategic instruments rather than as documentation formalize the reduction of unwarranted discretion (Eyetsemitan et al., 2022). Applied to hiring and promotion, this is the mechanism behind structured interviewing and calibrated review, and the operations literature supplies the measurement apparatus, in the form of process conformance rates and variability statistics, that these practices generally lack in D&I application. Lean Six Sigma applied in small enterprises demonstrates that the apparatus scales down to organizations without dedicated analytical functions (Ambali et al., 2021), which addresses the common objection that rigorous D&I measurement is available only to large firms.

Cycle time reduction in client onboarding illustrates the flow-based measurement approach at a granularity that D&I measurement rarely reaches (Oyeleye et al., 2022). The analogue is time-to-promotion measured as a distribution rather than a mean, disaggregated by group, which reveals disparities that promotion rate ratios conceal. Multi-stakeholder governance alignment work addresses the coordination problem where process ownership is distributed (Eyetsemitan et al., 2020), and the translation of regulatory requirements into operating procedure addresses the compliance interface (Eyetsemitan et al., 2021), which is the mechanism by which a disclosure obligation becomes an actual change in how decisions are made rather than an additional reporting task.

5.10 Human capital formation and the upstream pipeline

Firms frequently attribute weak representation to pipeline supply. The claim is testable and the education literature supplies the evidence base for testing it.

Comparative analysis of educational attainment and access identifies where cohort attrition actually occurs in the formation pipeline (Boakye et al., 2021), which is the necessary input to any availability benchmark. A firm claiming supply constraint is making an implicit assertion about this distribution, and the assertion is frequently wrong at the relevant seniority and geography. Integration of information technology and mathematical pedagogy addresses the quantitative skills pipeline specifically (Boakye et al., 2020), relevant to technical role availability.

Special education research contributes the most methodologically developed treatment of individualized measurement in this literature. Data-driven individualized education programme development formalizes the construction of individual-level goals with explicit measurement plans and periodic review against them (Yeboah & Oloto, 2022), which is a more rigorous individual development apparatus than most corporate talent processes employ. Compliance frameworks under disability education legislation demonstrate how a legal accommodation obligation is operationalized into documented, auditable practice (Oloto & Yeboah, 2022), which is directly transferable to workplace accommodation, an area of D&I practice that is almost entirely unmeasured despite carrying direct legal exposure. Pedagogical strategies for students with specific learning needs contribute the intervention design (Bobga et al., 2018), and student progress monitoring supplies the measurement cadence (Yeboah et al., 2022).

Teacher professional development and competency research addresses the capability of the people delivering the intervention (Yeboah et al., 2019), which corresponds to manager capability in the D&I context and is a stronger predictor of outcomes than programme design. Parental collaboration research demonstrates measurement of a stakeholder relationship that resists direct observation (Ogbona et al., 2020b), and coaching and career transition work addresses the mobility pathways that structure advancement (Ogbona et al., 2020a). Cross-cultural communication research contributes the measurement of interaction quality across difference (Lilian et al., 2020), which is the construct that inclusion scales attempt to capture at the organizational level. Data-informed learning platform frameworks and real-time educational analytics contribute the instrumentation (Orise & Niniola, 2020; Orise & Niniola, 2022), demonstrating continuous rather than periodic measurement of a developmental process.

5.11 Health equity and access measurement

Health services research has the most developed literature on equity measurement of any applied field, because access disparities are directly observable in utilization data and the outcome stakes are unambiguous. Infrastructure-driven expansion of diagnostic access demonstrates the measurement of an equity outcome through changes in the population able to reach a service (Aminu-Ibrahim et al., 2020), which is a genuine access metric rather than a proxy. The structural insight is that access is determined by facility siting, capacity, and operating model rather than by stated policy, and that measuring the policy tells you nothing about the access. The D&I parallel is the difference between having an inclusive policy and having a process people can actually use. Capital project delivery models for high-risk health facilities address the investment evaluation question in a setting where the return is partly social (Aminu-Ibrahim et al., 2019), and sustainable diagnostic laboratory infrastructure work addresses the durability of that investment (Aminu-Ibrahim et al., 2018). Laboratory spatial planning, regulatory-compliant design for molecular facilities, sustainable materials and energy efficiency, risk-managed construction, and design standards with operational planning collectively demonstrate how a social access objective is decomposed into engineering and operational specifications that are individually measurable

(Ogbete et al., 2018; Ogbete et al., 2019; Ogbete et al., 2020; Ogbete et al., 2021; Ogbete et al., 2022). This decomposition is the discipline that D&I commitments most conspicuously lack.

Health system financing research contributes the coverage and provider payment perspective (Ilodigwe & Adesemoye, 2019a), and the conceptual bridging from molecular science to health system outcomes illustrates the multi-level attribution problem in a field that has confronted it explicitly (Ilodigwe & Adesemoye, 2019b). Pharmacy-led delivery and access models demonstrate the measurement of a service redesign intended to reach underserved populations (Ilodigwe & Adesemoye, 2020), and governance and analytics work on the health system data backbone addresses the infrastructure prerequisite (Ilodigwe & Adesemoye, 2021), which corresponds to the human resource information system prerequisite for D&I analytics.

Last-mile distribution research addresses the specific problem of reaching populations that standard delivery models systematically miss (Asiedu & Asiedu, 2022), a structure that recurs in workforce contexts wherever a programme designed for the centre fails to reach peripheral or non-standard employment groups. Drug interaction risk frameworks in antenatal care illustrate systematic risk assessment for a population defined by a protected characteristic (Asiedu, 2022). Drug shortage early warning systems and regulatory readiness maturity models contribute the anticipatory measurement approach (Eze et al., 2022a; Eze et al., 2022b), and integration of biomarker and imaging parameters for cardiovascular risk stratification demonstrates the construction of a composite index with validated components and a defined outcome, which is the standard that D&I composite indices should be held to and are not (Okwah, 2022).

5.12 Energy justice and distributional metrics

The energy transition literature has developed explicit distributional measurement because the transition imposes costs and confers benefits unevenly, and because the unevenness is politically salient. This is the closest available model for measuring the distributive dimension of a corporate investment. Co-optimization of technical performance and community affordability formalizes the trade-off between an efficiency objective and a distributional objective within a single optimization rather than treating the distributional criterion as a constraint applied afterward (Komi & Adeniji, 2020). This is the methodological move that D&I evaluation most needs. A firm that optimizes for cost and then applies a diversity constraint will reach a different and generally worse solution than one that includes the distributional objective in the optimization directly.

Wind power forecasting work that connects grid stability to market equity demonstrates that a technical performance metric and an equity metric can be derived from the same model rather than from separate systems (Komi, 2021). Interpretable machine learning for failure prediction addresses the explainability requirement that arises whenever a model output affects a protected interest (Komi & Adamolekun, 2021), which is the same requirement that governs algorithmic hiring and promotion tools. Systematic review of control architectures contributes the centralization question (Komi & Adamolekun, 2022), relevant to whether D&I accountability should sit centrally or with business units, a question usually decided by organizational preference rather than by evidence. Battery storage research in weak-grid regions addresses measurement where infrastructure quality is itself unequal (Komi & Ganiu, 2022), and smart grid architecture work under high renewable penetration contributes the system integration perspective (Adenuga, 2022).

5.13 Condition monitoring and the leading-indicator problem

The engineering literature on condition monitoring addresses the same problem as leading indicators in safety, with a fully developed instrumentation apparatus, and it clarifies what a

leading indicator actually is. The transition from reactive to predictive maintenance is the canonical case (Sunday et al., 2020). Reactive maintenance responds to failure, which is a lagging indicator; predictive maintenance monitors condition variables whose degradation precedes failure, and the analytical work consists of establishing which observable variables carry that predictive content. Smart fault detection using sensor-based monitoring demonstrates the instrumentation (Sunday & Omoegun, 2022), and thermodynamic efficiency and control strategy work shows how performance degradation is measured continuously rather than at failure (Sunday et al., 2019). The lesson for D&I measurement is that a leading indicator is not simply an earlier measurement of the same thing; it is a different variable, validated against the terminal outcome. Corporate D&I practice frequently mislabels an earlier composition measurement as a leading indicator, which it is not. Non-destructive testing research contributes the inspection design question of how much to inspect, where, and how often, given that inspection is costly and imperfect (Atta et al., 2021; Atta et al., 2020). This is the sampling design problem for pay equity review and for promotion decision audit, where full population review is expensive and risk-weighted sampling is the practical alternative. Welding inspection standards and quality assurance work formalizes the qualification of the inspection process itself (Atta et al., 2022), which corresponds to the validation of an audit method, and green corrosion inhibitor research illustrates the substitution problem in which an intervention chosen on one criterion must be evaluated against others (Atta et al., 2018). Solar integration and hybrid load distribution work contributes the design of measurement in systems with variable inputs (Sunday & Omoegun, 2018; Sunday & Omoegun, 2019). Remote sensing research contributes the coverage dimension. Unmanned aerial vehicle applications in transmission line inspection demonstrate the substitution of comprehensive automated observation for sampled manual observation (Dagodzo, 2018b; Dagodzo, 2018a), pipeline and corridor monitoring extends this to linear assets (Dagodzo & Ahiaeke Patrick, 2020), and integrated frameworks combining aerial survey, laser scanning, and geographic information systems demonstrate multi-source data fusion (Dagodzo & Ahiaeke Patrick, 2021b). Geographic information system applications in asset management contribute the spatial data architecture (Dagodzo & Ahiaeke Patrick, 2021a), encroachment detection illustrates automated exception identification (Dagodzo & Ahiaeke Patrick, 2022), and deep learning applied to vegetation classification demonstrates automated pattern recognition at scale (Dagodzo et al., 2022). The organizational network analysis of Section 4.6 is structurally the same move: comprehensive passive observation replacing sampled active inquiry, with the same gains in coverage and the same governance obligations.

5.14 Regulatory compliance benchmarking and oversight design

Comply-or-explain disclosure regimes of the kind described in Section 4.2 rest on assumptions about how organizations respond to oversight. The regulatory compliance literature examines those assumptions. Predictive compliance monitoring frameworks demonstrate that inspection findings across an oversight population contain systemic signal that individual findings do not (Adeyelu, 2018), which is an argument for regulators to analyze the pattern of disclosure across firms rather than assessing each disclosure in isolation. Adaptive safety management system implementation models address the capability gap in resource-constrained settings (Adeyelu, 2019), which bears on the disproportionate compliance burden that standardized disclosure places on smaller firms. Comparative benchmarking models for certification compliance formalize cross-

entity comparison where local conditions differ (Adeyelu & Dagodzo, 2022), the central difficulty in cross-jurisdictional D&I comparison.

Risk quantification models for low-probability high-consequence events demonstrate estimation where the outcome is too rare to support direct measurement (Adeyelu, 2020), which is the situation for severe discrimination and harassment outcomes, where incidence is low, reporting is incomplete, and the standard response is to report the count without modelling the reporting process. Frameworks for managing encroachments and unauthorized structures illustrate enforcement against gradual boundary erosion (Adeyelu, 2021; Adeyelu, 2022), a structure that recurs in the slow drift of an organization away from a stated commitment.

Cybersecurity research contributes the adversarial and architectural perspective. Security audit and enterprise risk assessment frameworks specify the assessment structure (Dosunmu & Ogundele, 2019), intrusion detection and prevention models address continuous monitoring (Dosunmu & Ogundele, 2020), incident response and forensics address the post-event process (Dosunmu & Ogundele, 2021), and threat intelligence integration demonstrates the use of external signal in internal risk assessment (Dosunmu & Ogundele, 2022). Operational technology security research contributes the convergence problem, in which two systems with different governance histories must be assessed under one framework (Adegbite et al., 2022; Adegbite et al., 2020), which describes the integration of human resource and financial reporting systems that assured workforce disclosure requires. Zero trust architecture contributes the design principle that access should be verified continuously rather than granted once (Ahmed et al., 2021), which applied to demographic data governance means that authorization to view sensitive workforce data should be evaluated per access rather than per role. Adversarial machine learning research establishes that a model deployed in a contested environment will be attacked through its inputs (Adebayo et al., 2022), which is the formal statement of the gaming problem for any metric that becomes consequential. Lifecycle risk assessment in offshore production contributes the long-horizon evaluation structure (Falegan & Aniebonam, 2022), relevant to the lag problem of Section 7.

5.15 Enterprise information systems as the data substrate

Every claim in this paper about what firms should measure presumes a system of record capable of producing the measurement reproducibly. That presumption is frequently false, and the enterprise systems literature explains why.

Platform governance frameworks establish the controls that keep a configurable business system consistent as it evolves (Badmus et al., 2019b), and version control and deployment pipeline research demonstrate the reproducibility apparatus (Badmus et al., 2022a; Badmus et al., 2018). The relevance is direct: a workforce metric is reproducible only if the definitions embedded in the reporting system are themselves versioned, and most human resource reporting environments cannot state which definition produced a figure published two years earlier. Extract, transform, and load design work addresses the integration of records from multiple sources into a consistent analytical layer (Badmus et al., 2019a), which is the practical obstacle to linking demographic, compensation, performance, and exit data into the person-period dataset that the estimators of Section 4 require. Comparative deployment framework analysis (Badmus et al., 2020) and enterprise service bus integration research (Badmus et al., 2022b) address the multi-system case.

Directory services and identity infrastructure work supplies the authoritative person record on which all workforce analysis depends (Ladapo et al., 2019), and digital transformation practice research addresses the organizational change required to make such systems authoritative rather than nominal (Ladapo et al., 2022b). Offline assessment research contributes the observation that

measurement systems must function where connectivity and infrastructure are limited (Ladapo et al., 2018), relevant to global workforce measurement in operations outside corporate centres. Capacity planning and resource utilization forecasting demonstrate the operational forecasting apparatus (Edivri & Oteri, 2022), and service delivery and security operations research addresses the sustained operation of the systems that produce the data (Ogbole et al., 2021; Okoruwa et al., 2020).

5.16 Rural and agricultural inclusion measurement

Agricultural economics has measured inclusion in production systems for longer than corporate D&I has existed as a field, and under harder data conditions.

Gender inclusion and equity across agricultural value chains is measured through participation, control of assets, and returns at each stage rather than through headcount at any single point (Michael & Ogunsola, 2022b). This value chain decomposition is precisely the flow-based logic of Section 4.4 applied to an economic rather than an organizational hierarchy, and it produces the same analytical benefit, which is the identification of the specific stage at which participation diverges. Access to finance research contributes the credit constraint analysis (Michael & Ogunsola, 2019a), a structural barrier with no direct workplace analogue but with a close parallel in access to sponsorship and to stretch assignments, which function as the internal capital of a career. Socioeconomic barriers to technology adoption among smallholders demonstrate the measurement of differential uptake of an ostensibly universal intervention (Michael & Ogunsola, 2022a), which is the dosage and coverage problem at Layer 2 of the framework in Section 8. Extension services research addresses the intermediated delivery of a capability (Michael & Ogunsola, 2021e), structurally identical to manager-mediated delivery of a workplace programme, where the intermediary's own capability and incentives determine reach. Climate-smart practice research links adoption to household outcomes over multi-year horizons (Michael & Ogunsola, 2021d), an example of the long-horizon outcome measurement that D&I evaluation requires and rarely attempts. Data-driven policy models and policy alignment analysis contribute the framework linking intervention to system-level outcome (Michael & Ogunsola, 2021c; Michael & Ogunsola, 2021a), digital agriculture research addresses inclusive system design (Michael & Ogunsola, 2021b), and agribusiness education research addresses the skills pipeline (Michael & Ogunsola, 2019b). Related work in agricultural engineering and animal science illustrates the underlying measurement discipline. Factor analysis applied to machine performance demonstrates the decomposition of an aggregate outcome into weighted contributing variables (Bello et al., 2022b), the same technique underlying the confirmatory factor analysis of Section 4.3, and performance evaluation of purpose-built equipment illustrates the specification of measurement criteria before construction rather than after (Bello et al., 2022a). Controlled feeding trials with graded treatment levels demonstrate dose-response estimation under experimental control (Aye & Tawose, 2015; Aye & Tawose, 2016), which is the design that organizational research can rarely achieve and should approximate where it can. Phenotypic characterization across regions demonstrates systematic measurement of population heterogeneity (Ekeocha et al., 2021), the methodological ancestor of the dispersion indices discussed in Section 3.1.

5.17 Multi-objective weighting and the composite index problem

The composite index problem identified in Section 3.2 is formally a multi-objective optimization problem, and the engineering optimization literature treats it as such.

Multi-algorithm formulations of single-objective and multi-objective functions for electrical machine design make the weighting question explicit, showing that the optimal design depends entirely on the relative weight assigned to loss, weight, and cost objectives, and that no weighting is technically privileged (Amayo, 2017; Amayo & Popoola, 2017a; Amayo et al., 2015). The parallel to composite D&I indices is exact and unflattering. A provider that aggregates representation, policy existence, and disclosure completeness into one score has chosen a weighting, that weighting determines the ranking, and the choice is neither disclosed nor defended. The engineering treatment at least states the objective function.

Voltage control research under distributed generation demonstrates system management where control is dispersed among many actors with individual objectives (Oshevire et al., 2017), which describes a devolved D&I accountability model. Telecommunications deployment research on service quality contributes the measurement of a service attribute experienced individually but delivered systemically (Amayo & Popoola, 2017b), which is the structural form of inclusion as a construct.

5.18 Policy alignment and institutional frameworks

Corporate D&I commitments increasingly interact with national and supranational policy frameworks, and the policy alignment literature addresses the resulting coordination problem.

Policy alignment modelling for climate diplomacy demonstrates the reconciliation of domestic objectives with international commitments where the two are measured differently (Liadi, 2022a), the structure that a multinational face in reconciling group-level commitments with jurisdictionally specific legal constraints. Continental integration frameworks address measurement across member entities with heterogeneous capacity (Liadi, 2022b), and peacebuilding effectiveness frameworks confront outcome measurement where the outcome is contested, long-horizon, and confounded by factors outside any actor's control (Liadi, 2022c). The last of these is methodologically closest to D&I impact evaluation, and its central lesson is that effectiveness frameworks in such domains are most credible when they measure process fidelity and intermediate outcomes explicitly rather than claiming terminal effects they cannot identify.

5.19 Recurring methodological commitments

Six things transfer from these literatures to D&I evaluation. The first is the leading indicator discipline of Sections 5.1 and 5.13, which requires that an early metric be a different variable validated against the terminal outcome rather than an earlier measurement of the same one. The second is the attribution apparatus of Section 5.4, which supplies estimators for multi-touch, multi-period interventions. The third is the assurance architecture of Sections 5.2, 5.3, and 5.15, which specifies what a metric must satisfy to be audited and what systems must exist to produce it. The fourth is the distributional optimization of Section 5.12, which includes the equity objective in the optimization rather than applying it as an afterward constraint. The fifth is the flow decomposition of Sections 5.9, 5.11, and 5.16, which locates disparity at a specific stage rather than reporting it in aggregate. The sixth is the adversarial framing of Sections 5.3 and 5.14, which assesses a metric by how it behaves when a rational agent optimizes against it.

None of these is present in the disclosure frameworks that standardized D&I measurement between 2020 and 2022. That absence, rather than any shortage of statistical technique, is the substance of the field's measurement problem.

6. Criteria for assessing metric quality

Table 2 sets out criteria against which a D&I metric can be assessed. They are drawn from measurement theory, from audit practice, and from the failure modes documented in the preceding sections.

Table 2. Evaluation criteria for D&I metrics

Criterion	Question it answers	Common failure
Construct validity	Does the metric measure the construct it names?	Representation percentages presented as measures of inclusion
Measurement invariance	Does it mean the same thing across the groups compared?	Cross-group survey mean comparison without invariance testing
Reliability	Would repeated measurement give the same result?	Single-item measures; small-cell estimates with wide confidence intervals
Sensitivity to intervention	Can it move within the evaluation horizon in response to action?	Board composition as a programme metric, when board turnover is a multi-year process
Attributability	Can change in it be linked to a specific investment?	Aggregate representation trends credited to a training programme
Resistance to gaming	Does optimizing the metric advance the goal?	Junior-heavy hiring inflating aggregate representation while senior attrition worsens
Assurability and privacy compliance	Is it reproducible from auditable systems within legal constraints?	Metrics requiring demographic categories that cannot lawfully be collected in some jurisdictions

Resistance to gaming deserves particular emphasis. Goodhart's law, in its familiar formulation, holds that when a measure becomes a target it ceases to be a good measure. D&I metrics are unusually exposed to this dynamic because the most visible metrics are the most easily manipulated. Aggregate workforce representation responds fastest to high-volume junior hiring, which is also the least expensive lever and the least indicative of equitable process. A firm can improve its headline number for several consecutive years while its promotion and senior attrition differentials deteriorate. Any evaluation framework that does not report flows alongside stocks is structurally vulnerable to this substitution.

7. Constraints on measurement

Endogeneity. The core inferential obstacle is that firms select into D&I investment. Profitable, growing, well-governed firms in tight labor markets invest more and also perform better for unrelated reasons. Without exogenous variation, no amount of statistical sophistication recovers a causal estimate.

Simultaneity and reverse causation. Inclusion perceptions and performance are jointly determined. Employees in successful units report better climate partly because success is pleasant. Panel data with unit fixed effects and lagged specifications mitigate this only partially.

Long and variable lags. Composition responds to process change on a horizon measured in years, since it is the integral of flow changes. Evaluation windows of one to two years, which match

budget cycles, are structurally mismatched to the phenomenon and systematically understate effects. This mismatch creates a bias toward funding interventions with fast-moving proxy metrics.

Small cells and intersectionality. Intersectional analysis is where the substantive action lies and where statistical power is weakest. A cell containing a small number of employees produces estimates with confidence intervals too wide to support inference and cannot be published without re-identification risk. Suppression thresholds, typically requiring a minimum cell size before reporting, remove precisely the observations of greatest interest. Hierarchical Bayesian models with partial pooling across cells offer partial relief by borrowing strength across related groups, but this remained rare in corporate practice through 2022.

Cross-jurisdictional data constraints. A multinational cannot construct a globally consistent metric. France restricts collection of ethnic and racial statistics on constitutional grounds. Germany's data protection regime and works council structures constrain what may be collected and how it may be analyzed. Many jurisdictions have no analogue to the EEO-1 categories, which are in any case specific to United States social history and travel poorly. GDPR classifies data revealing racial or ethnic origin as a special category requiring a specific lawful basis. The practical consequence is that global aggregate diversity figures published by multinationals are typically constructed from inconsistent underlying definitions and heavy imputation, a fact rarely disclosed.

Self-identification data quality. Voluntary self-identification produces non-random missingness. Disclosure rates for disability, sexual orientation, and gender identity are strongly conditional on perceived psychological safety, meaning that disclosure rates are themselves an inclusion signal and simultaneously a source of bias in every metric that depends on them. Rising measured representation may reflect rising disclosure willingness rather than changing composition, and these two interpretations have opposite implications for programme evaluation.

Rater and instrument bias. Performance ratings, which serve as controls in most pay and promotion models, are themselves potentially biased. Conditioning on a biased mediator biases the estimated direct effect. This point has been made repeatedly in the context of expert testimony on workplace bias, and it remains the most consequential specification error in applied corporate pay equity work.

The disclosure-validity paradox. The metrics that regulators mandate and index providers standardize are the demographic stock measures, because they are objectively verifiable and cross-firm comparable. The metrics with the strongest documented association with firm outcomes are perception-based and process-based measures, which are neither easily verified nor comparable across firms. Standardization has therefore concentrated on the least informative measures. Resolving this tension is the central open problem in the field.

8. Matching estimators to evaluation layers

The preceding sections imply that no single model answers the evaluation question. What is required is an explicit chain in which each layer of the investment logic is matched to an estimator capable of identifying quantities at that layer, with the identifying assumptions stated at each step. Table 3 sets out the correspondence.

Table 3. Correspondence between evaluation layers, estimators, and identifying assumptions

Layer	Question	Primary estimator	Identifying assumption	Illustrative metric
1. Input	What was committed?	Activity-based costing including opportunity cost of participant and leader time	Complete cost capture, including uncosted internal time	Fully loaded cost per programme, per participant, per business unit
2. Activity	What was delivered, to whom?	Coverage and dosage analysis, treatment fidelity assessment	Accurate exposure records	Percentage of eligible population exposed; dosage distribution; delivery fidelity index
3. Proximal outcome	Did experience and behavior change?	Validated latent scales with measurement invariance; ONA structural metrics; pre-post designs with comparison units	Invariance holds; comparison units satisfy parallel trends	Inclusion scale scores by group; cross-group tie density; sponsorship access
4. Process outcome	Did allocation become more equitable?	Transition matrix estimation by group; Cox hazard models; Oaxaca-Blinder decomposition; causal ML on high-dimensional controls	Unconfoundedness given the control set; controls are not themselves biased mediators	Promotion rate ratio by group and grade; conditional attrition hazard ratio; adjusted and unadjusted pay gap
5. Terminal outcome	What value was created or preserved?	Monetized cost avoidance via utility analysis; impact-weighted employment accounts; quasi-experimental estimates where exogenous variation exists	Effect size at Layer 4 is causally identified; monetization parameters are defensible	Avoided replacement cost; monetized opportunity and diversity impact; steady-state composition projection versus target

Three properties of this arrangement bear emphasis. First, each layer is independently informative, so that a firm unable to identify effects at Layer 5 can still establish at Layer 4 that its promotion rate ratio moved, which is a materially stronger claim than any representation percentage. Second, claims propagate upward only with stated assumptions: a Layer 5 monetary figure is valid conditional on a Layer 4 causal estimate, and reporting a return figure without the corresponding Layer 4 identification is the most common error in practitioner evaluation. Third, joint reporting constrains gaming, because a requirement to report flow metrics alongside any composition figure renders the junior-hiring substitution described in Section 6 immediately detectable.

The arrangement carries a resource implication, since it is more demanding than a dashboard. The appropriate response is portfolio concentration, in the sense of Section 4.9: fund fewer

interventions at sufficient scale to permit staggered rollout and credible comparison, rather than many interventions that can only ever be described.

9. Discussion

For practice. The dominant corporate metric set as of 2022 measured the wrong layer. Firms should report flow metrics, specifically promotion rate ratios and conditional attrition hazards by group and grade, alongside every composition figure. Where interventions are deployed across multiple units, staggered rollout should be adopted by default, since the marginal cost is low and the inferential gain is large. Pay equity analysis should report adjusted and unadjusted gaps together, with the control set disclosed and justified. Inclusion surveys should undergo measurement invariance testing before any cross-group comparison is published.

For investors and rating providers. Composite scores that aggregate disclosure quantity, demographic composition, and policy existence into one number have low construct validity and weak convergent validity across providers. Reporting component sub-scores separately, disclosing weightings, and separating disclosure completeness from substantive performance would improve interpretability more than any refinement of the aggregation.

For standard setters and regulators. The CSRD and its associated standards represented the most significant development of the focal period, principally because they extended assurance requirements to workforce metrics. Assurance forces definitional discipline. The open question is whether standard setters can extend comparable rigor to process metrics, which are more informative than stock metrics but less easily verified. A promotion rate ratio computed from a firm's HR information system is auditable in principle. Requiring it would materially improve the evidentiary base.

For research. Four priorities follow from the review. First, applied use of modern staggered-adoption DiD estimators in corporate settings, where two-way fixed effects specifications remain the norm despite known bias. Second, systematic study of the disclosure-validity paradox, specifically whether verifiable process metrics can be constructed with better outcome association than demographic stocks. Third, hierarchical Bayesian approaches to the intersectional small-cell problem. Fourth, measurement invariance evidence for the widely used inclusion scales across national and cultural contexts, which is currently thin and which conditions the validity of every multinational inclusion comparison. Several limitations qualify these conclusions. The review presents no new empirical estimates, so its claims about the relative performance of estimator's rest on the cited literature rather than on direct comparison. Its scope is weighted toward large listed firms in the United States and Europe, reflecting where both the regulatory activity and the research literature concentrate, and the applicability of the layered scheme to small firms, to state-owned enterprises, and to jurisdictions with different legal treatment of demographic data is untested. The focal period ends in 2022, and the literature can be expected to develop further, particularly on the perception-versus-demographics question and on the contested legal status of mandated diversity disclosure in the United States. The layered scheme set out in Table 3 is a synthesis rather than a validated instrument, and its practical value awaits application.

10. Conclusion

The period culminating in 2022 produced a genuine advance in the quantitative evaluation of corporate diversity and inclusion investment, but the advance was not the arrival of a superior metric. It was a change in what is treated as the object of measurement. Three shifts define it: from stocks to flows, from demographic composition to validated experience, and from correlational association to explicit counterfactual identification.

The evidence assembled here supports three conclusions. First, the metric most widely reported and most heavily standardized, aggregate demographic representation, has the weakest documented association with firm outcomes and is the most easily gamed. Second, the estimators capable of supporting causal claims exist and are well developed, but require variation in treatment timing that firms can create at low cost and mostly choose not to. Third, the field's central structural problem is the disclosure-validity paradox, in which the pressure toward comparability drives standardization onto the least informative measures.

The layered scheme set out above does not dissolve these problems. Its purpose is narrower and, in the current state of practice, more useful, which is to make the evidentiary status of any D&I claim explicit, so that a monetized return figure cannot be presented without the causal estimate it depends on, and a representation figure cannot be presented without the flow data that determine whether it is sustainable. A field that reports its assumptions can be corrected. One that reports only its numbers cannot.

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