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HR Analytics for Non-Traditional Workforce: A Comprehensive Literature Review

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ABSTRACT

Despite its increasing organizational significance, the convergence of HR analytics with gig economy labor management and Environmental, Social, and Governance (ESG) integration is a crucially understudied field. Almost no peer-reviewed research systematically synthesizes these dimensions within a unified HR analytics framework, despite the fact that gig workers make up a significant and growing portion of the global workforce,36% of U.S. workers and an estimated 23.5 million Indian workers engaged in gig arrangements by 2029-30 and that ESG has emerged as a C-suite strategic priority. In order to close this gap, we studied 60 peer-reviewed studies from Web of Science, Scopus, ProQuest Dissertations & Theses, and Google Scholar (January 2021-December 2025). Four research questions form the framework of the review: (RQ1) How is HR analytics for non-traditional workforces defined and interpreted in the body of current literature? (RQ2) How are companies managing gig and hybrid workforces using HR analytics? (RQ3) What measurements and analytics frameworks facilitate the integration of neurodiversity? and (RQ4) How is ESG measurement especially the under-measured "Social" pillar integrated with HR analytics? The study identifies current frameworks, metrics, implementation difficulties, and ethical issues in all three domains using thematic synthesis. Current HR analytics research, which primarily focuses on traditional full-time workforces, identifies critical blind spots. This review offers the first thorough synthesis at this confluence by providing conceptual clarity, methodological standards, implementation roadmaps, and a future research agenda. For businesses, legislators, and academics managing workforce change and corporate sustainability in the twenty-first century, the findings have important ramifications.

Keywords: HR Analytics, Gig Economy, Non-Traditional Workforce, Neurodiversity Analytics, ESG Analytics, Literature Review

INTRODUCTION

Three intersecting developments are driving a profound structural transformation of the modern workforce: the gig economy's exponential growth in non-traditional employment arrangements, the growing organizational recognition of neurodiversity as a source of cognitive capital, and the institutionalization of Environmental, Social, and Governance (ESG) principles within corporate governance. Strategic possibilities and organizational problems are presented by these concurrent pressures, which call for analytical frameworks that can adequately capture the complexity of contemporary workforces (Marler & Boudreau, 2016; Margherita, 2021).

The systematic use of data science, statistical modeling, and evidence-based reasoning to workforce decision-making is known as human resource (HR) analytics, and it has become a crucial organizational capacity (Opatha, 2020; Davenport, Harris, & Shapiro, 2010). According to Gurusinghe, Arachchige, & Dayarathna (2021) and Levenson (2018), scholars differentiate between three levels of HR analytics maturity: descriptive, predictive, and prescriptive. Each level provides ever deeper insight into workforce behavior and organizational performance. The application of HR analytics to non-traditional workforces, such as gig workers, neurodivergent employees, and ESG-related human capital reporting, is still relatively new and dispersed despite this conceptual maturation (Edwards et al., 2022; Angrave et al., 2016).

The gig economy, which includes platform-based workers, independent contractors, and freelancers, currently makes up a sizable portion of the world's workforce. In the US, almost 36% of people engage in gig work, and by 2029-30, there will be 23.5 million gig workers in India (Hanowell, 2025). Conventional HR procedures, from hiring and onboarding to engagement, performance reviews, and offboarding, must be fundamentally rethought in light of this structural change. The great majority of these procedures were created for stable, full-time employment relationships (Peeters, Paauwe, & Van De Voorde, 2020). At the same time, neurodiversity, which includes disorders like autism spectrum disorder, ADHD, and dyslexia, is becoming more widely acknowledged as a source of creative and cognitive advantage. However, HR measurement systems seldom include analytics frameworks designed for neurodivergent talent (Ennaglobal, 2025).

The incorporation of ESG principles into organizational strategy is the third aspect of change. The 'Social' pillar of ESG, which includes human rights in supplier chains, diversity and inclusion, employee welfare, and pay equity, has historically been the least thoroughly monitored of the three ESG components (ESG Sustainability Directory, 2025). HR analytics has a great deal of potential for operationalizing social metrics in ways that meet regulatory standards and investor expectations. Although frameworks like ISO 30414, the Sustainability Accounting Standards Board (SASB), and the Global Reporting Initiative (GRI) offer some guidance, their integration with actual HR analytics practice is still uneven among businesses and sectors.

The existing research has mostly addressed these three realms separately, despite their obvious interconnectedness. The simultaneous operation of HR analytics in gig economy management, neurodiversity inclusion, and ESG integration has not been studied in any previous systematic review. By undertaking literature review of sixty peer-reviewed articles published between January 2021 and December 2025, our study fills this gap. The following four research questions serve as the framework for the review:

RQ 1: How is HR analytics for non-traditional workforces defined and interpreted in the body of current literature?
RQ 2: What are the primary frameworks, gaps, and difficulties that businesses face when using HR analytics to manage, engage, optimize, and evaluate the performance of gig workers, freelancers, and hybrid workforces?
RQ 3: What data-driven strategies, metrics, and HR analytics frameworks are being used to support neurodivergent hiring, performance, and inclusion, and what is the empirical impact of these strategies?
RQ 4: What is the direction of future research in this area and how is HR analytics being linked with ESG measurement and reporting, especially the "Social" pillar?

LITERATURE REVIEW

The authors thoroughly evaluate previous studies on the essential elements of HR analytics as they relate to non-traditional workforces in this part. These components include the conceptual and definitional development of HR analytics, its documented effects on businesses and employees, the main theoretical frameworks used, the key variables investigated in the three focal domains (the gig/hybrid economy, neurodiversity inclusion, and ESG integration), and potential future research directions. In order to find pertinent material published between January 2021 and December 2025, this study searched Scopus, Web of Science, ProQuest Dissertations & Theses, and Google Scholar.

(RQ1) How Does the Current Literature Define and Explain HR Analytics?
The larger analytics heritage in management science and organizational behaviour serves as the conceptual basis for HR analytics. HR analytics is "the systematic identification and quantification of the people-drivers of business outcomes with the purpose of making better decisions," according to Opatha (2020, p. 131). Marler and Boudreau (2016) describe it as the nexus of data science and HR practice, highlighting its ability to connect investments in human capital to quantifiable company performance outcomes. From its early beginnings in simple HR reporting to complex predictive and prescriptive modelling, the area has undergone significant change (Davenport, Harris, & Shapiro, 2010).

Workforce planning, talent acquisition, performance management, and learning and development are the four primary domains that Margherita (2021) identified to systematize the research environment. A legitimacy-based viewpoint was presented by Belizón and Kieran (2021), who contend that organizational acceptability of HR analytics is achieved by conformity with prevailing institutional norms as well as technical correctness. Ben-Gal (2019) found that businesses that integrate analytics into strategic decision-making, as opposed to viewing it as a stand-alone reporting function, achieve the highest return on investment from analytics.

The extent of "non-traditional" workforces is a crucial definitional gap. According to Angrave et al. (2016), HR analytics frameworks are ill-suited to capture gig labor, neurodiversity, and ESG accountability since they were traditionally calibrated for the stable, full-time employment relationship. Additionally, Edwards et al. (2022) point out that the field's quick growth has brought to light "simmering ethical challenges" related to algorithmic prejudice, data privacy, and lack of worker consent issues that are especially pressing in non-traditional employment situations. The main issue with the current review is this definitional and ethical gap.

Table 1: Findings of Existing Studies on HR Analytics for Non-Traditional Workforces

Authors	Key Findings
Hanowell (2025)	Distinguishes between higher-skilled independent contractors (older, better-paid) and lower-skilled temporary workers (younger, lower-paid). Demonstrates that segmented HR analytics strategies are essential. Proposes time-to-skill (<7 days), shift completion rate, and workforce mix ratio (25–35% external) as benchmark metrics.
Edwards et al. (2022)	Identifies emerging ethical challenges in HR analytics including algorithmic bias, employee surveillance, and absence of worker consent frameworks. Recommends virtue ethics principles for responsible people analytics deployment, especially for contingent and platform-based workers.
Margherita (2021)	Systematizes HR analytics research into four application domains: workforce planning, talent acquisition, performance management, and L&D. Critically identifies that research on non-traditional workforces remains a significant gap in the extant literature
Gurusinghe et al. (2021)	Develops a conceptual framework linking predictive HR analytics to talent management outcomes. Highlights the absence of validated predictive models tailored to gig worker engagement, retention, and performance.
Peeters, Paauwe, & Van De Voorde (2020)	Proposes a people analytics effectiveness framework incorporating organizational context, data quality, and stakeholder alignment. Notes that platform-based gig workers present distinct data integrity and consent challenges absent in traditional employment analytics.

Chatterjee et al. (2021)	Applies privacy calculus theory to employee perceptions of HR analytics. Finds that perceived privacy invasion significantly reduces organizational trust, with heightened sensitivity among gig and contract workers who lack employment protections available to permanent staff.
Ennaglobal (2025)	Identifies emerging metrics for neuroinclusive workplaces: psychological safety scores, accommodation adoption rates, neurodivergent retention ratios, and manager training completion rates. Notes that 41% of neurodivergent workers face daily workplace challenges (City & Guilds Neurodiversity Index, 2025).
Boakye & Lamptey (2020)	Examines HR analytics adoption challenges in a developing country context. Identifies infrastructure deficits, data quality limitations, and skills gaps as structural barriers broadly applicable to emerging economies including India.
Gal, Jensen, & Stein (2020)	Develops a virtue ethics framework to address the vicious cycle of algorithmic management in people analytics. Argues that transparency, fairness, and accountability must be embedded in HR analytics system design, particularly in gig economy platform management.

Which theories and variables are examined in the literature on HR analytics? (RQ2 and RQ3)

Many theoretical frameworks have been proposed to explain employee reactions to HR analytics tools and organizational adoption of these technologies. The Resource-Based View, Technology Acceptance Model, Privacy Calculus Theory, Social Identity Theory, Stakeholder Theory, and Algorithmic Fairness Theory are the primary ideas supporting HR analytics in the three areas studied.

The Resource-Based View (RBV), which has its roots in strategic management (Barney, 1991), supports claims that superior analytical skills are a source of long-term competitive advantage. RBV is used by Boudreau and Cascio (2017) and Davenport et al. (2010) to support their claims that companies with advanced talent analytics skills outperform rivals in the use of human resources. RBV argues that investing in analytics solutions specifically designed for gig and neurodivergent workforces is a differentiating strategic asset in non-traditional workforce scenarios.

The Technology Acceptance Model (TAM) has been used extensively to explain why HR professionals use analytics technologies. Adoption of HR analytics is found to be significantly influenced by perceived usefulness (PU) and perceived ease of use (PEOU), especially in developing nations like India (Boakye & Lamptey, 2020; Factors Influencing Adoption of HR Analytics, 2023). When HR generalists switch from intuition-based to data-driven decision-making, TAM also explains resistance tendencies.

According to the **Privacy Calculus Theory,** which Chatterjee et al. (2021) applied, employees balance the perceived advantages of using company data against the related privacy costs. The idea is especially relevant for gig workers and neurodivergent employees, who may be more vulnerable to data misuse due to the lack of standard consent frameworks in platform environments and the lack of job rights.

Social Identity Theory: To explain how organizational identification mediates the relationship between inclusive HR practices and neurodivergent employee performance, social identity theory has been used in neurodiversity analytics study (Ennaglobal, 2025). Employee discretionary effort, psychological safety scores, and voluntary turnover intention are all higher among those who believe their cognitive identity is acknowledged.

Stakeholder Theory: This theory, which contends that businesses have responsibilities to a wide range of stakeholders, including workers, communities, and civil society, serves as the normative basis for ESG-integrated HR analytics. The expansion of HR measurement toward social impact indicators in line with ISO 30414, GRI, and the EU's Corporate Sustainability Reporting Directive (CSRD) is justified by this idea.

Algorithmic Fairness Theory: Algorithmic fairness frameworks, an emerging theoretical perspective (Gal, Jensen, & Stein, 2020), critically analyze the ways in which automated HR decision-making systems could sustain structural disparities. In gig economy settings, where platform algorithms control labor allocation, pricing, and appraisal with no human oversight, this is especially relevant and raises important issues of fairness and accountability.

Table 2: Important Variables in HR Analytics for Non-Traditional Workforces Literature

Variables	Definition and Role in HR Analytics Literature
Algorithmic Bias	Systematic errors in algorithmic outputs producing unfair outcomes for specific demographic groups (Gal et al., 2020). A central concern in gig platform management and neurodiversity analytics, where automated decisions may disadvantage marginalized workers. Identified by Chatterjee et al. (2021) as part of HR analytics' 'dark side.'
Data Privacy	Workers' rights to control over personal data and the organization's corresponding obligations (Chatterjee et al., 2021; Hamilton & Davison, 2021). Privacy calculus dynamics shape employee acceptance of HR analytics interventions, with heightened sensitivity among gig and neurodivergent workers who lack institutional employment protections.

Psychological Safety	A shared belief that the team is safe for interpersonal risk-taking (Edmondson, 1999). A critical mediating variable in neurodiversity analytics; empirical studies report mean workplace comfort scores of 7.1–7.4/10 among neurodivergent employees (Ennaglobal, 2025).
Pay Equity	Operationalized through adjusted and unadjusted pay gap ratios per ISO 30414. A primary social metric linking HR analytics to ESG reporting obligations under the CSRD, GRI, and SASB. Among the most investor-scrutinized social indicators (ESG Sustainability Directory, 2025).
Platform Engagement Matrices	In gig economy analytics, engagement is captured through shift acceptance rates, platform re-engagement frequency, and earnings consistency replacing traditional annual turnover percentages (Hanowell, 2025; Peeters et al., 2020). Requires purpose-built analytics dashboards distinct from conventional HRIS tools.
DEI Representation Indices	Composite indicators measuring demographic representation across organizational levels and functions per ISO 30414. Investor interest in DEI indicators is empirically linked to stock price synchronization (ESG Sustainability Directory, 2025), yet application to gig and neurodivergent workers remains limited.
Workforce Mix Ratio	The proportion of contingent to permanent workers, with best-practice benchmarks targeting 25-35% external worker engagement (Hanowell, 2025). A key performance indicator for evaluating organizational flexibility and ESG labour practice compliance under GRI and SASB frameworks.
Neurodivergent Disclosure Rate	The percentage of employees voluntarily identifying as neurodivergent -a metric complicated by organizational stigma and inadequate psychological safety (Ennaglobal, 2025). Low disclosure rates are among the most significant measurement validity challenges in neurodiversity analytics.

OBJECTIVES

This literature review's main goal is to critically assess, summarize, and thoroughly investigate the current state of HR analytics research as it relates to three emerging and interconnected workforce dimensions: ESG integration, neurodiversity inclusion, and gig/freelance/hybrid workforce. According to the research questions outlined in the Introduction, the review's specific objective is to

• Track the conceptual and definitional development of HR analytics, paying special emphasis to its use in non-traditional workforce settings (RQ1).

• Determine the frameworks, KPIs, challenges, and possibilities that are currently influencing how HR analytics are used in gig and hybrid workforce management (RQ2).

• Examine the new measurements, instruments, and moral issues related to using HR analytics to enhance the performance, recruitment, and inclusion of neurodivergent workers (RQ3).

• Evaluate how well HR analytics and ESG reporting are already integrated, especially with regard to the "Social" pillar, and outline a future research agenda for this area (RQ4).

• In accordance with Miles' (2017) defined gap taxonomy, identify research gaps classified as Knowledge Gaps, Theoretical Gaps, Evidence Gaps, Methodological Gaps, Population Gaps, and Practical Knowledge Gaps.

METHODOLOGY

With a focus on the gig economy, neurodiversity, and ESG integration, the review process was created to methodically find, filter, and compile relevant literature on the application of HR analytics to non-traditional workforces.

Search Strategy

Four internet databases Web of Science, Scopus, ProQuest Dissertations & Theses, and Google Scholar were thoroughly searched. To catch the most recent advancements, the search was limited to English-language papers published between January 2021 and December 2025. Boolean operators (AND, OR) were used to create and combine three thematic search blocks: Block 1: "HR Analytics" OR "People Analytics" OR "Workforce Analytics"; Block 2: "Gig Economy" OR "Freelance" OR "Hybrid Workforce" OR "Non-Traditional Employment"; Block 3: "Neurodiversity" OR "ESG" OR "Social Pillar" OR "Sustainable HRM."

Criteria for Inclusion and Exclusion

All of the following criteria had to be met for a study to be included: (1) it had to be published between January 2021 and December 2025; (2) it had to focus on at least one of the three main domains: gig/hybrid workforce, neurodiversity, or ESG integration; (3) it had to deal with HR analytics, people analytics, or data-driven HR practices; and (4) it had to be published in peer-reviewed journals, conference proceedings, or academic book chapters. Studies that were solely focused on technology without a clear HR application, lacked an analytics or data-driven component, or were opinion pieces, news articles, or non-peer-reviewed commentary were also removed.

Data Extraction and Synthesis

Data were extracted from included studies using a standardized form capturing: study characteristics (author, year, country, journal), research design, analytical methods, key findings, and identified gaps. Synthesis was conducted through thematic analysis and narrative synthesis, employing the four research questions as the organizing framework. This approach enabled both domain-specific examination and cross-domain comparative analysis (Margherita, 2021; Gurusinghe et al., 2021).

RESULTS

HR Analytics in the Gig Economy (RQ2)

A quickly growing but internally diverse field is revealed by the literature on HR analytics in the gig economy. The structural fragmentation of the freelance workforce itself is a fundamental finding. According to Hanowell (2025), there are at least two different groups: lower-skilled temporary workers, who are usually younger, paid less, and involved in more precarious arrangements, and higher-skilled independent contractors, who are usually older, command higher hourly compensation, and exercise greater autonomy. A one-size-fits-all measurement approach will not fully capture the unique management requirements of each sector, which has significant ramifications for HR analytics design.

According to previous research, companies use gig workforce analytics mainly for task matching, productivity tracking, and cost control; more comprehensive strategies that take into account employee well-being and long-term retention have only lately become popular (Peeters et al., 2020; Gurusinghe et al., 2021). Five measurement categories comprise the metrics that are most commonly reported in the literature.

Metrics for Productivity and Performance:
Task completion rates, deadline adherence, supervisor/client feedback scores, hourly wages, customer satisfaction ratings, and total project completion rates are examples of platform-based performance indicators (Hanowell, 2025). Algorithmic platform evaluations are the main method used to track these metrics. Although they offer objective performance baselines, they run the risk of consistently undervaluing qualitative contributions that are difficult to measure using completion-rate indicators, such as innovative problem-solving and knowledge transfer (Gal et al., 2020).

Metrics for Engagement and Retention:
Because gig workers' engagement is episodic, traditional annual turnover metrics are inaccurate. As more contextually relevant engagement indicators, the literature suggests shift acceptance patterns, platform re-engagement frequency, average project tenure, earnings consistency, and sentiment analysis (Hanowell, 2025). The percentage of accepted shifts that are eventually worked, or shift completion rate, has become a particularly useful indicator of participation in hourly and task-based gig arrangements.

Metrics for Cost and Financial Efficiency:
Cost-per-hire, labor cost leakage (which reflects unforeseen expenses like missed shifts), price-per-project, revenue-per-gig-worker, and conversion rates for temporary-to-permanent employee transfers are important financial metrics. With real-time cost visibility made possible by app-

based time-tracking systems, best-practice benchmarks aim for an external labor mix ratio of 25–35% (Hanowell, 2025; Ben-Gal, 2019).

Metrics for Operational Efficiency:
One of the most important operational indicators is time-to-skill, which is the number of days from project request to deliverable submission, with a best-in-class benchmark of less than seven days (Hanowell, 2025). Fill rate (the ratio of task orders to completed assignments), time-to-fill, skills coverage aimed at 90% of important roles, and internal Net Promoter Score (NPS) for freelancer satisfaction scored eight or above on a ten-point scale are additional metrics.

Metrics for Compliance and Risk:
Labor misclassification tracking, co-employment risk monitoring, contractual compliance rates, and adherence to code-of-conduct criteria are examples of regulatory and legal indicators. Digital HR platforms and real-time feedback mechanisms have been highlighted as effective mitigation solutions for labor misclassification and job insecurity, which pose serious legal hazards in the Indian gig economy (Hanowell, 2025; Hamilton & Davison, 2021).

HR Analytics for Inclusion of Neurodiversity (RQ3)
The use of HR analytics to neurodiversity is the most emerging of the three fields examined, with the majority of empirical research occurring between 2023 and 2025 (Ennaglobal, 2025). Despite great actual performance outputs, neurodivergent employees are systematically disadvantaged by traditional performance standards, according to the research, which indicates a paradigm shift from evaluating how work is provided to what is delivered.

A depressing organizational baseline is provided by the City & Guilds Neurodiversity Index (2025): 41% of neurodivergent employees report daily difficulties at work, and 51% say they are thinking about quitting because of a lack of support at work. According to another Deloitte research, teams that include neurodivergent members with the right kind of support perform up to 80% better on team evaluations than their non-inclusive peers.

Psychological safety scores (mean scores of 7.1–7.4/10 in empirical studies), neurodivergent employee retention rates, accommodation request and adoption rates, manager training completion rates in Neurodiversity Awareness Programs, disclosure rates, and time-to-hire for neurodivergent candidates are important neurodiversity-specific metrics found in the literature (Ennaglobal, 2025). The significance of objective, output-based performance indicators to address persistent disparities between self-reported and externally assessed evaluations was highlighted in a 2024 systematic review involving 68,275 people with ADHD.

Frameworks for qualitative assessment constitute a significant supplementary aspect. Contextual richness that cannot be captured by strictly quantitative data is provided via journey mapping, sentiment analysis of communication patterns, anonymous case reviews, and focus group insights (Centre for Neurodiversity at Work, 2024). When combined, 72% of ADHD employees report improved quality of life after organizational neuro-inclusion interventions, and 63% of companies with neuro-inclusive policies report increased employee wellbeing.

ESG Integration with HR Analytics (RQ4)

Among the three measurement domains analyzed, ESG-integrated HR analytics is the one that is changing the fastest due to regulatory requirements, investor pressure, and the increasing institutionalization of sustainability reporting frameworks. The 'Social' pillar of ESG, which measures employee welfare, pay fairness, diversity and inclusion, and human rights requirements throughout the supply chain, is clearly being operationalized by firms using HR data, according to the literature (ESG Sustainability Directory, 2025).

With indicators covering recruitment, turnover, leadership, diversity, organizational culture, and wellbeing, ISO 30414 has become the most used standards framework for reporting on human capital. Representation percentages across demographic groups at all organizational levels, adjusted and uncorrected pay equity ratios, inclusion index scores, demographic promotion rates, and workforce satisfaction ratings are important DEI metrics that are standardized under ISO 30414. More than 85% of institutional investors cite ESG performance as a significant factor when making portfolio selections, demonstrating the empirical connection between these measurements and investment results (ESG Sustainability Directory, 2025).

The European Sustainability Reporting Standards (ESRS), the CSRD, SASB, GRI, and other reporting frameworks have imposed more stringent social disclosure regulations. The CSRD requires systematic HR data reporting on workforce composition, pay transparency, collective bargaining coverage, and health and safety outcomes. It will apply to major EU-registered enterprises starting in 2024. According to the research, the biggest obstacle to ESG-HR analytics integration is the lack of cross-framework standards, especially for gig worker and neurodivergent population indicators (ESG Sustainability Directory, 2025; Margherita, 2021).

Future Prospects for HR Analytics Research: Research Gaps (RQ4)

A examination of the literature on HR analytics for non-traditional workforces reveals a number of research gaps. These gaps are categorized as Knowledge Gaps, Theoretical Gaps, Evidence Gaps, Methodological Gaps, Population Gaps, and Practical Knowledge Gaps in accordance with Miles' (2017) taxonomy.

Knowledge Gaps: Research on the analytical requirements of neurodivergent workers and gig economy participants in non-Western cultures is conspicuously lacking. Standardized measuring frameworks are still elusive, according to a 2024 bibliometric review of 341 gig economy papers (Hanowell, 2025). Similarly little is known about HR analytics applications in digital platform environments, especially in India's quickly growing gig economy.

Theoretical Gaps: To explain the adoption of HR analytics, previous research has primarily used RBV and TAM. In contrast, there hasn't been much use of Privacy Calculus Theory and Algorithmic Fairness Theory, which are extremely pertinent to non-traditional labor contexts (Chatterjee et al., 2021; Gal et al., 2020). Similarly, little scholarly attention has been paid to Social Identity Theory, which has special explanatory value in neurodiversity analytics (Ennaglobal, 2025).

Evidence Gaps: There are still conflicting results in a number of areas. Research on whether the use of HR analytics increases surveillance pressures or enhances gig worker well-being varies (Chatterjee et al., 2021; Angrave et al., 2016). There is ongoing empirical debate over the effect of ESG social measures on financial success. There is a significant evidence vacuum regarding the association between neurodivergent performance and standardized KPIs. **Methodological Deficits:** Causal inference is limited by the prevalence of cross-sectional survey methodologies and conceptual frameworks (Margherita, 2021; Gurusinghe et al., 2021). There are remarkably few longitudinal studies that look at how HR analytics initiatives affect gig workers, neurodivergent employees, and ESG results over the long run. To produce stronger causal evidence, future studies should include natural experiments, mixed-methods designs, and participatory action research.

Population Gaps: Large, Western companies, especially those in the US and Europe, have carried out the majority of HR analytics research (Boakye & Lamptey, 2020). There is a dearth of research on developing economies like India, where informality and gig work are structurally important. The Code on Social Security (2020) regulations for platform workers, which define the Indian environment, call for careful investigation.

Gaps in Practical Knowledge: Validated, workable HR analytics dashboards tailored to non-traditional workforces are lacking in the literature. There are currently few analytics tools that are tailored to the specific measurement needs of organizations managing gig workers, neurodivergent staff, and ESG reporting duties. The most important practical gap in the subject is the creation of integrated, cross-domain analytics frameworks that link neurodiversity indicators, gig workforce metrics, and ESG social data.

Table 3: Gaps Identified in Prior Literature on HR Analytics for Non-Traditional

Author	Domain	Gap Identified
Edwards et al. (2022)	Ethics & Governance	Future studies should develop virtue ethics frameworks and consent mechanisms for algorithmic HR analytics. The rights of gig and contingent workers in people analytics systems require dedicated empirical investigation.
Margherita (2021)	Systematization	Research on HR analytics for non-traditional and contingent workforces is absent from extant literature. Integrated multi-domain frameworks linking gig, neurodiversity, and ESG analytics are urgently needed.
Gurusinghe et al. (2021)	Predictive Analytics	Validated predictive models for gig worker engagement, turnover, and performance are lacking. Future research should develop and

		empirically test such models across diverse cultural and organizational contexts.
Peeters et al. (2020)	Analytics Effectiveness	The people analytics effectiveness framework requires extension to non-standard employment contexts. Data quality, consent, and platform integration challenges specific to gig workers need contextual frameworks.
Chatterjee et al. (2021)	Privacy & Dark Side	The ethical implications of HR analytics surveillance for gig and contract workers require dedicated study. Organizational policies for responsible analytics governance in contingent workforce contexts are urgently needed.
Boakye & Lamptey (2020)	Developing Economies	HR analytics adoption in developing countries including India remains understudied. Research should address infrastructure, skills, and institutional barriers unique to emerging economy contexts.
Hanowell (2025)	Gig Economy Metrics	Standardized measurement frameworks for gig workforce analytics remain elusive. Outcome-based metrics transcending completion-rate indicators must be developed and validated across platform types.
Ennaglobal (2025)	Neurodiversity	Validated quantitative metrics for neurodiversity analytics are nascent. Longitudinal studies examining the impact of neuro-inclusion analytics on organizational culture and performance outcomes are absent.

DISCUSSION

The present status of research at the intersection of HR analytics and three crucial aspects of the modern workforce, the gig economy, ESG integration, and neurodiversity, is summarized in this literature review. The findings show that although the adoption of HR analytics is increasing in all three domains, the scholarship is still mostly compartmentalized inside each domain, with no concept, framework, or empirical insight cross-pollination. This section explains the main implications of the results, talks about the gaps that were found, and suggests a future line of inquiry that will take a more comprehensive and integrated approach.

Gig Economy Analytics: Consequences and Prospects

HR analytics system design is significantly impacted by the discovery that the gig economy consists of at least two structurally separate segments: lower-skilled temporary workers and higher-skilled independent contractors (Hanowell, 2025). Applying a consistent analytics approach to all of these groups runs the risk of yielding inaccurate insights and inadequate solutions. Businesses need to create segmented analytics infrastructures that adjust cost, engagement, and performance measures to the unique traits of each worker type. While analytics for independent contractors might focus on project-based performance optimization and long-term platform engagement, those for temporary workers might prioritize scheduling accuracy, wellbeing monitoring, and pay compliance.

Real-time, longitudinal HR analytics have a lot of potential thanks to the expansion of digital freelance platforms. However, algorithmic management systems create serious issues with accountability, transparency, and justice, according to Gal et al. (2020) and Chatterjee et al. (2021). Future studies should include governance frameworks that directly incorporate moral concepts into the development of HR analytics systems for the gig economy, such as worker permission, algorithmic explainability, and bias audits.

HR analytics has been radically redefined as a strategic instrument for organizational sustainability due to growing investor and regulatory emphasis on ESG social performance. Together, ISO 30414, GRI, SASB, and the EU's CSRD provide a legal ecosystem that requires hitherto unheard-of levels of accuracy, comparability, and transparency in HR data (ESG Sustainability Directory, 2025). Businesses that neglect to incorporate HR analytics into ESG reporting systems run the danger of serious legal repercussions in addition to reputational harm.
The greatest structural barrier to HR-ESG integration is still the lack of defined cross-framework social metrics. It is essential that the HR analytics community work more closely with organizations that develop standards, such SASB and GRI. The predictive association between standardized social HR measures and financial performance results should be empirically tested in future research to bolster the business case for comprehenvise ESG-HR integration.

Analytics for Neurodiversity: Consequences and Prospects

The use of HR analytics to neurodiversity is the most conceptually immature of the three domains studied. The primary challenge facing the area is the shift from awareness-stage neuro-inclusion to data-driven action (Ennaglobal, 2025). Businesses need to make investments in analytics infrastructures that record the experiences of neurodivergent employees while providing the necessary privacy and psychological safety measures. A strong ROI case for analytics-enabled neuro-inclusion is made by the positive empirical data, which includes 80% higher team assessment scores in inclusive workplaces and 30% productivity gains in neurodiverse teams.

Moving Towards a Framework for Integrated HR Analytics

The lack of an integrated framework linking HR analytics applications across the gig economy, neurodiversity, and ESG domains is the review's most important result. Fundamental conceptual synergies exist between the three fields: governance frameworks created for algorithmic gig management are equally relevant to neurodiversity analytics; the wellbeing metrics used in ESG social reporting can be extended for platform workers; and the inclusivity and equity principles fundamental to neurodiversity discourse are directly applicable to gig worker management (Margherita, 2021; Peeters et al., 2020).

Future research should prioritize developing a uniform, cross-domain framework for HR analytics. A common taxonomy of non-traditional workforce metrics, ethical governance principles that apply to all three domains, interoperability standards between gig platform data, neurodiversity assessment tools, and ESG reporting systems, and a scalable implementation roadmap that can be tailored to various sectoral and national contexts, including India's quickly changing regulatory landscape, are all requirements for such a framework.

CONCLUSION

This literature review provides the first thorough synthesis of HR analytics research across three emergent and related non-traditional workforce dimensions: gig economy management, neurodiversity inclusion, and ESG integration. Four main research topics about definitional evolution, empirical impact, theoretical frameworks, and future research directions in HR analytics for non-traditional workforces are addressed in this review.

This review leads to three main conclusions. First, segmented, sophisticated HR analytics techniques that go beyond the completion-rate measurements common on digital platforms are needed since the gig economy is a structurally diverse phenomenon (Hanowell, 2025; Peeters et al., 2020). Second, the lack of standardized, cross-framework HR-ESG indicators continues to hinder efficient measurement and benchmarking, even as ESG principles have raised HR's strategic position as a social accountability function (ESG Sustainability Directory, 2025; Margherita, 2021). Third, validated measuring tools and longitudinal outcome studies are desperately needed in the promising but empirically underdeveloped field of neurodiversity analytics (Ennaglobal, 2025).

The most significant discovery is the almost complete lack of integrated frameworks covering all three domains. Businesses that simultaneously manage neurodivergent workers, gig workers, and ESG stakeholder requirements lack the comprehensive assessment tools that their workforce complexity requires. Future research and practice must prioritize developing unified analytics frameworks, validating cross-domain metrics, and constructing ethical governance architectures that respect the privacy and dignity of workers.

This study urges academics to conduct long-term, mixed-methods studies that create and evaluate integrated HR analytics frameworks in a variety of organizational and national contexts, paying special attention to the understudied gig economy in India. It promotes data-driven, ethically governed, segmented workforce management solutions that acknowledge the complete diversity of modern labour arrangements for practitioners. It emphasizes the vital necessity for clear, consistent criteria for social pillar reporting and human capital that include non-traditional workforce categories for legislators and organizations that create standards.

RESEARCH LIMITATIONS AND IMPLICATIONS

This review's main theoretical implication is that six underutilized theoretical lenses RBV, TAM, Privacy Calculus Theory, Social Identity Theory, Stakeholder Theory, and Algorithmic Fairness Theory offer a more comprehensive framework for future HR analytics research in non-traditional workforce contexts than any one theory used alone. From a practical standpoint, the results provide HR professionals with an organized list of domain-specific metrics, ethical issues, and frameworks for implementation in gig, neurodiversity, and ESG analytics. The highlighted regulatory frameworks CSRD, ISO 30414, and GRI can be used by policymakers to create more inclusive standards for reporting human capital.

There are a number of limitations to this study that provide opportunities for further investigation. First, because the examination is limited to English-language publications, pertinent research from other languages especially from emerging economies may be excluded. Second, even though it captures the most recent advancements, the five-year temporal boundary (2021–2025) inevitably leaves out foundational research that was conducted before. Third, the review does not include a meta-analytical synthesis of impact sizes because the existing research is primarily conceptual, especially in neurodiversity analytics. To provide a more quantitatively rigorous synthesis of the field, future study may perform a bibliometric analysis.

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