From Instinct to Intelligence: People Analytics as a Framework for Human-Centred HRM in Nigerian Manufacturing Organizations

Sunday Onuminya Yusuf., Christopher Chinedu Okpara., Dr. Ibrahim Aminu Mohammed., Florence Nkonye Akinrinlola., Paul Shaibu Akogwu., Mohammed Aliyu Haladu

Business Administration, University of Jos, Jos, Plateau, Nigeria

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ABSTRACT

Purpose — Nigerian manufacturing HRM remains intuition-driven, applying uniform motivational strategies to an occupationally diverse workforce lacking data infrastructure. This article argues that people analytics applied to motivation and satisfaction data provides the methodological foundation for human-centred HRM consistent with Society 5.0's vision of technology serving individual flourishing.

Aims — The article maps motivation–satisfaction evidence onto the four-level people analytics maturity model, develops a phased implementation roadmap for Nigerian industrial contexts, and constructs an ethical risk matrix ensuring analytics serves worker flourishing rather than surveillance.

Design/methodology/approach — A cross-sectional survey of 144 employees across Lagos, Kano, and Port Harcourt employed validated instruments (Cronbach α = .76–.93), hierarchical regression, and moderation analysis (PROCESS macro), mapped as a proof-of-concept across descriptive, diagnostic, predictive, and prescriptive analytics levels. The study demonstrates how conventional survey methodology, when designed with occupational granularity, can populate each tier of the people analytics maturity model without requiring longitudinal or big-data infrastructure.

Findings — Mean job satisfaction was M = 3.14 (SD = 0.86), concealing substantial heterogeneity. Working conditions and recognition were primary drivers (β = .19; β = .15); 34.7% of workers were educationally underemployed (d = 0.58); technical staff (M = 3.42) reported markedly higher satisfaction than non-skilled workers (M = 3.02).

Originality/value — The first empirically grounded people analytics framework for Nigerian manufacturing HRM, with an ethical risk matrix calibrated to structural inequalities, occupational hazards, and union relations.

Keywords: people analytics, human-centred HRM, Nigerian manufacturing, Society 5.0, workforce segmentation, ethical analytics

Paper type: Research paper

INTRODUCTION

The promise of people analytics—using data and evidence to make HR decisions that improve both organizational performance and employee wellbeing—has been extensively theorized in Western organizational contexts. A systematic review of 122 research papers identified people analytics as an evidence-based approach that uses technology to analyse employee data to improve HRM and overall business performance (Belizón et al., 2024). Yet both the scholarly literature and industry practice have concentrated predominantly in high-income, high-technology environments, leaving a critical question unanswered: what does people analytics look like—and what can it deliver—in the resource-constrained, labour-intensive industrial organizations that constitute the backbone of Nigeria's manufacturing sector?

Nigerian manufacturing is both among the most consequential and least analytically served of the country's formal sectors. With a workforce operating under physically demanding conditions, compressed wages relative to financial and telecommunications sectors, and occupational structures that concentrate non-skilled production workers at the base of steep positional hierarchies, manufacturing organizations face HRM challenges that are qualitatively distinct from service sector equivalents. Yet HR practice in most Nigerian manufacturing organizations remains what Ellmer and Reichel (2021) call the 'one-size-fits-all approach'—uniform motivational strategies applied to a heterogeneous industrial workforce without the data infrastructure to differentiate production workers from technical staff, new hires from long-tenure machine operators, or underemployed graduates from well-matched tradespeople.

This article argues that people analytics provides exactly the methodological foundation needed to transition Nigerian manufacturing HRM from instinct-driven to intelligence-driven practice—and that this transition constitutes the organizational expression of the Society 5.0 vision within industrial contexts. Society 5.0 envisions a human-centred society in which advanced technology serves individual human flourishing rather than organizational efficiency optimization alone (Breque et al., 2021; Maddikunta et al., 2022). Industry 5.0 extends this to the workplace, emphasizing that technological capability should amplify human strengths, protect human dignity, and produce equitable outcomes across diverse workforce segments (Gamberini et al., 2024). In manufacturing environments characterized by physical risk, skill stratification, and often adversarial industrial relations, human-centred HRM is not a luxury but an operational and ethical imperative.

A survey of 144 Nigerian manufacturing employees reveals a satisfaction deficit that uniform HRM approaches both produce and perpetuate: manufacturing workers reported a mean satisfaction of M = 3.14, driven by acute deficiencies in working conditions, compensation equity, and organizational policy transparency. People analytics reframes what this finding contributes. Standard organizational behaviour research asks: what predicts manufacturing worker satisfaction? People analytics asks: how can that predictive knowledge be systematically collected, interpreted, and applied to improve HR decisions that address the specific motivational architecture of this sector?

The article makes three contributions. First, it provides the first empirically grounded people analytics implementation framework for Nigerian manufacturing organizations. Second, it introduces an ethical risk matrix calibrated to the power asymmetries, physical hazard contexts, and industrial relations dynamics specific to manufacturing—a contribution to the transparency and fairness discourse central to Society 5.0. Third, it demonstrates that classical motivation research can be reinterpreted through a people analytics lens to generate data-driven HRM intelligence without requiring the expensive technology infrastructure that current people analytics discourse implicitly assumes.

Theoretical Background

People Analytics: From Metrics to Intelligence

People analytics has evolved from rudimentary HR reporting—headcount, absenteeism, turnover rates—toward a sophisticated capability for predictive and prescriptive workforce intelligence. Belizón et al. (2024), in their systematic review, identify a knowledge discovery process comprising four progressively sophisticated analytical levels: descriptive (what is happening), diagnostic (why it is happening), predictive (what will happen), and prescriptive (what should be done). Most organizations, particularly in developing economies, operate at the descriptive level—producing dashboards of workforce metrics without the diagnostic or predictive capability to convert data into actionable intelligence (Habtamu et al., 2025).

In Nigerian manufacturing, the analytics maturity gap is particularly consequential. A production manager knowing that average satisfaction is 'moderate' across the plant floor cannot design targeted recognition or working conditions programs, allocate intervention resources by occupational segment, or anticipate turnover in high-skill technical roles. A diagnostic analytics capability reveals which motivational factors drive satisfaction for which sub-groups—production workers versus supervisors, long-tenure versus new entrants, well-matched versus overqualified employees. A predictive capability anticipates where satisfaction deterioration is emerging before it becomes a turnover or productivity event. The difference between descriptive and predictive capability is the difference between knowing a problem exists and knowing where it is forming and how to prevent it.

HR analytics research demonstrates that data-driven decision-making substantially outperforms instinct-based HR practice on key outcomes including turnover prediction, engagement improvement, and performance management effectiveness (McCartney & Fu, 2022; Di Prima et al., 2024). The empirical contribution of motivation–satisfaction research—typically treated as an end in itself within organizational behaviour scholarship—becomes instrumental input to the analytics pipeline when viewed through this lens.

Society 5.0 and Human-Centred HRM in Manufacturing Contexts

Society 5.0's vision of a human-centred society that harnesses technology to solve social challenges and improve quality of life has direct implications for how manufacturing organizations manage their human resources. As Gamberini et al. (2024) document, Industry 5.0 within the Society 5.0 framework positions the worker not as a production input to be optimized but as a human being whose flourishing is an end in itself. This represents a substantive departure from Industry 4.0's efficiency-first automation logic, and it aligns with calls in the HRM literature for a human-centred approach that gives priority to practices designed to enhance employee wellbeing (Cooke et al., 2022).

The human-centred HRM agenda is particularly consequential for manufacturing contexts. Production workers in Nigerian factories face concentrated occupational risks—physical hazard exposure, shift work disruption, noise and environmental stress, limited agency over work pace—that make both their wellbeing vulnerability and their motivational needs structurally distinct from office-based workers. A Society 5.0-aligned manufacturing HRM does not merely extend generic analytics frameworks to a new sector; it requires analytics capability specifically calibrated to the motivational architecture of physically demanding, hierarchically stratified industrial work.

The connection between people analytics and Society 5.0 values is not automatic. When demographic and position-level segmentation data is used to identify which manufacturing workers most need organizational investment—which production sections have the worst working conditions ratings, which tenure cohorts are most at risk of disengagement, which qualified employees are underutilized—it serves human-centred goals. When the same data is used to identify which workers to retain and which to replace based on predicted performance trajectories, it risks reproducing structural inequalities through algorithmic means. Establishing ethical guardrails is therefore a central challenge for Society 5.0-aligned manufacturing HRM.

The Equity, Transparency, and Fairness Imperative in Manufacturing

The ethical dimension of people analytics has received increasing scholarly attention as deployment has expanded. Belizón et al. (2024) identify ethics, data privacy, and algorithmic transparency as the most rapidly growing research theme in people analytics scholarship. In Nigerian manufacturing contexts, where structural inequalities along occupational grade, educational attainment, and seniority lines are empirically documented, the ethical stakes of demographic analytics are amplified by three sector-specific dynamics.

First, the physical power asymmetry between management and production workers in manufacturing environments creates conditions in which data collection can readily become surveillance. Workers on factory floors have less capacity to resist invasive monitoring than office workers, and the precedent of quality control data collection (production speed, error rates, attendance) means that the conceptual boundary between performance monitoring and personal data collection is already blurred. Analytics governance in manufacturing must actively protect this boundary.

Second, industrial relations dynamics in Nigerian manufacturing—including union presence in larger establishments and informal collective action in smaller ones—mean that analytics perceived as serving management's interests at workers' expense will encounter resistance that undermines the organizational trust analytics itself depends on. Transparency protocols must be designed for workforce populations with legitimate scepticism about management data initiatives.

Third, the qualification–fit problem in Nigerian manufacturing is acute and structurally produced. Graduate underemployment across the Nigerian economy means that a substantial proportion of manufacturing workers—estimated at 34.7% of the manufacturing sample—are educationally overqualified for their current roles, often as a result of economic necessity rather than vocational choice. Analytics that identifies overqualification without a corresponding organizational commitment to role enrichment risks producing labelling effects that further demotivate rather than address the underlying structural condition.

The Empirical Evidence Base

Study Overview

The empirical evidence informing this article derives from a cross-sectional survey of 144 permanent employees drawn from Nigerian manufacturing facilities in Lagos, Kano, and Port Harcourt—Nigeria's three principal manufacturing hubs—conducted between December 2025 and February 2026. Purposive sampling was employed to ensure representation across occupational grades; facilities were selected from food processing, textile, and metalwork sub-sectors. All participants were permanent, full-time employees with a minimum of six months' tenure, ensuring sufficient organizational experience to provide meaningful motivation and satisfaction assessments. Informed consent was obtained from all participants, and data were collected through structured questionnaires administered by trained research assistants during non-production periods to minimize response disruption.

Motivation was measured using adapted subscales from Herzberg et al.'s (1959) two-factor theory instrument and Hackman and Oldham's (1975) Job Diagnostic Survey, capturing intrinsic factors (recognition, meaningful work, autonomy, development opportunity) and extrinsic factors (working conditions, compensation equity, promotion opportunity, organizational policy). Job satisfaction was measured using the Minnesota Satisfaction Questionnaire short form (Weiss et al., 1967) and the Job Descriptive Index (Smith et al., 1969), yielding a composite five-facet satisfaction profile. All instruments were adapted for Nigerian manufacturing contexts, piloted with 20 employees, and refined for clarity. Internal consistency was satisfactory across all scales (Cronbach α = .76–.93).

Hierarchical multiple regression examined the overall motivation–satisfaction relationship, with demographic variables entered at Block 1 and motivational factor subscales at Block 2. Relative weight decomposition (Johnson, 2000) was applied to partition the unique and shared variance contributions of each motivational predictor, producing a rank-ordered importance profile independent of multicollinearity constraints. Moderation analysis using the PROCESS macro (Hayes, 2018, Model 1) tested whether demographic variables—age cohort, tenure group, and gender—significantly moderated the overall motivation–satisfaction slope, with simple slopes probed at high (+1 SD) and low (−1 SD) values of each moderator. Qualification–fit was assessed by comparing respondents' highest educational qualification against the minimum qualification specified for their current role; employees whose qualification exceeded the role requirement by one NQF level or more were classified as educationally underemployed. Group differences in satisfaction between well-matched and underemployed employees were tested using independent samples t-tests, and the practical effect size was computed as Cohen's d.

The manufacturing sample is occupationally structured into non-skilled production workers (42%), semi-skilled operatives (28%), technical and artisan staff (18%), and supervisory/managerial staff (12%)—a stratification that closely mirrors the occupational composition of Nigeria's formal manufacturing sector (National Bureau of Statistics, 2023). From a people analytics perspective, this occupational heterogeneity within a single sector is exactly the workforce segmentation challenge that analytics is designed to address.

Descriptive Analytics: The Manufacturing Satisfaction Landscape

Descriptive analytics establishes the satisfaction baseline and identifies where gaps exist. Manufacturing employees reported a mean job satisfaction of M = 3.14 (SD = 0.86)—a moderate score that aggregate reporting would treat as unremarkable, but which conceals acute within-workforce heterogeneity. Position level generated the largest satisfaction gap: technical and supervisory staff reported M = 3.42 while non-skilled production workers reported M = 3.02—a 0.40-point differential representing the systematic accumulation of motivational advantages at higher positions in the production hierarchy.

The compensation satisfaction dimension ($M = 2.76$, $SD = 1.18$) was the lowest-rated facet in manufacturing, reflecting the wage compression and below-market pay structures that characterize much of Nigeria's industrial sector. Promotion satisfaction ($M = 2.94$, $SD = 1.09$) was the second lowest-rated dimension. An organization relying on aggregate satisfaction scores would report 'moderate' workforce satisfaction and conclude that no urgent action is required. People analytics reveals that this aggregate conceals acute deficits among production workers in compensation equity and advancement opportunity that are both measurable and addressable.

Sector-level descriptive analytics produces an additional actionable finding: the high standard deviations on compensation (1.18) and promotion (1.09) satisfaction indicate that these are not universal experiences across manufacturing facilities. Some plants or organizational units have addressed these concerns more effectively than others. Identifying those units and replicating their practices is a diagnostic question that descriptive data alone cannot answer—but descriptive data is the necessary prerequisite that makes the diagnostic question visible.

Diagnostic Analytics: Why Satisfaction Varies and for Whom

Diagnostic analytics identifies the causal architecture driving satisfaction variation in manufacturing. The hierarchical regression reveals working conditions as the dominant satisfaction predictor ($\beta = .19$, RW = 11.3%), followed by recognition ($\beta = .15$, RW = 9.2%) and compensation equity ($\beta = .14$, RW = 8.1%). This diagnostic profile reflects the structural realities of manufacturing work: the physical environment of production directly shapes worker wellbeing in concrete, measurable ways, while shift-level acknowledgement and pay fairness constitute the two motivational levers that manufacturing HR functions can most directly influence within existing resource constraints.

Overall, employee motivation explained 51.8% of job satisfaction variance ($R^2 = .518$, $F = 39.87$, $p < .001$). Manufacturing-specific moderation analysis reveals that motivation–satisfaction associations vary significantly by career stage ($B = 0.44$ at age 20–29 to $B = 0.68$ at age 50+), tenure ($B = 0.42$ for < 1 year to $B = 0.61$ for > 10 years), and gender ($B = 0.45$ for female vs. $B = 0.57$ for male). These differential slopes mean that equal motivational investment produces unequal satisfaction returns across workforce segments—a finding with direct resource allocation implications that only analytics can surface.

The qualification–job fit analysis is particularly diagnostic for manufacturing. Employees identified as educationally underemployed— 34.7% of the manufacturing sample—reported satisfaction 0.58 standard deviations below well-matched employees ($d = 0.58$, $p < .001$). Importantly, underemployed manufacturing workers showed heightened sensitivity to development opportunities ($r = .64$ vs. $.49$ for well-matched employees) and autonomy ($r = .56$ vs. $.42$). The diagnostic implication is clear: underemployed graduates on factory floors do not primarily need higher wages to close their satisfaction gap—they need role enrichment, skill deployment pathways, and developmental progression that existing manufacturing job designs frequently fail to provide.

Predictive and Prescriptive Analytics: From Diagnosis to Decision

A critical methodological note governs this section: the present study is cross-sectional, and cross-sectional moderation slopes cannot themselves constitute predictive analytics findings in the longitudinal sense the maturity model implies. What the study contributes at the predictive level is more precisely described as empirically grounded parameters for future predictive use—a proof-of-concept demonstration that motivation–satisfaction survey data, when designed with occupational granularity and moderation analysis, can populate the predictive tier once replicated longitudinally. The distinction matters for scientific integrity: the slopes reported here are demonstrated cross-sectional differentials, not forecasts validated against future outcomes.

With that framing established, the cross-sectional moderation results provide the most empirically credible starting parameters currently available for Nigerian manufacturing predictive analytics. The motivation–satisfaction slope varies from $B = 0.42$ among employees with less than one year's tenure to $B = 0.61$ among those with more than ten years—a demonstrated differential indicating that the same unit improvement in working conditions is associated with meaningfully larger satisfaction gains for long-tenure workers than for new entrants. These slopes are directly usable as provisional predictive parameters: a manufacturing HR function that knows the tenure distribution of each facility can estimate the expected satisfaction impact of a planned working conditions intervention, subject to longitudinal validation. Similarly, the career stage moderation (B = 0.44 at age 20–29, rising to B = 0.68 at age 50+) suggests differential cohort responsiveness to motivational investment that, once replicated in longitudinal designs, would enable targeted sequencing of recognition and working conditions programs across facilities with different workforce age profiles.

Prescriptive analytics translates diagnostic and predictive findings into evidence-grounded recommended actions for manufacturing HR. The relative weight decomposition findings provide a natural prescriptive priority ranking, ordered by each factor's demonstrated contribution to satisfaction variance. Working conditions improvement is the highest-priority structural intervention: its relative weight (RW = 11.3%) reflects its greatest unique variance contribution among all motivational predictors, and its direct organizational controllability makes it the most consequential lever available within existing resource constraints. Recognition—shift-level acknowledgement, safety performance commendation, peer-nomination schemes—ranks second (RW = 9.2%): empirically demonstrable as strongly salient among production-grade employees, low-cost, and scalable across facilities without capital expenditure. Compensation equity review (RW = 8.1%) ranks third: the high within-facility standard deviation on compensation satisfaction (SD = 1.18) indicates that compensation concerns are addressable through policy consistency and transparency rather than necessarily through wage increases alone. Prescriptive analytics thus converts the diagnostic evidence directly into a priority-ordered intervention sequence calibrated to both effect size and resource feasibility.

Mapping The Evidence to People Analytics Maturity Levels

Table 1 maps the empirical evidence from the Nigerian manufacturing motivation–satisfaction study to each level of the people analytics maturity model, demonstrating the analytical intelligence each level unlocks and how conventional survey-based research—when designed with analytics application in mind—can populate the entire maturity ladder without requiring big data infrastructure.

Table 1 People Analytics Maturity Mapping: Evidence from Nigerian Manufacturing Motivation–Satisfaction Study (n = 144*)*

Analytics Level	**Conventional PA Approach**	**Manufacturing Evidence Base**
Descriptive	Headcount, absenteeism, turnover dashboards	Satisfaction means by occupational grade and tenure cohort (M = 2.76–3.42); compensation and promotion dimensions lowest-rated; non-skilled production workers M = 3.02 vs. technical/supervisory staff M = 3.42
Diagnostic	Exit interviews; engagement surveys identifying why satisfaction varies	Hierarchical regression identifying working conditions (β = .19) and recognition (β = .15) as primary satisfaction drivers; 34.7% underemployment with d = 0.58 satisfaction penalty; moderation slopes by career stage (B = 0.44–0.68)
Predictive	Turnover risk scoring; flight risk identification by segment	Motivation–satisfaction slopes by tenure/career segment enabling prediction of satisfaction change per unit motivational improvement; working conditions sensitivity especially high for long-tenure workers (B = 0.61)
Prescriptive	Recommended interventions for identified risk segments; targeted resource allocation	Evidence-ranked intervention sequence: working conditions improvement (RW = 11.3%) as highest-priority structural intervention; recognition programs (RW = 9.2%) as highest-priority intrinsic intervention; compensation equity review (RW = 8.1%); role enrichment for underemployed graduates; equity audit before budget allocation

Note. PA = people analytics. Statistics derived from hierarchical regression with relative weight decomposition, moderation analysis, and qualification–fit comparison reported in Section 3. The four maturity levels follow Belizón et al.'s (2024) knowledge discovery process framework.

Three observations emerge from Table 1. First, the progression from descriptive to prescriptive analytics in manufacturing does not require technology upgrades at early stages—it requires analytical capability applied to existing survey data. Nigerian manufacturing organizations already conducting annual engagement surveys have the raw material for descriptive and diagnostic analytics; what they typically lack is the statistical expertise to convert those surveys into prescriptive intelligence.

Second, the prescriptive level requires the ethical framework discussed in Section 5. Prescribing differentiated interventions based on occupational grade data creates ethical exposure—particularly in manufacturing environments where grade boundaries intersect with ethnicity, gender, and educational background in ways that can reproduce structural inequalities if analytics outputs are used carelessly.

Third, the manufacturing analytics journey has a natural Nigerian sequencing. Descriptive analytics is achievable within six months using existing survey tools and basic SPSS or Excel. Diagnostic capability requires moderation analysis—achievable with standard statistical training and the PROCESS macro. Predictive capability is grounded in the present study's moderation slopes, which provide cross-sectionally demonstrated parameters that serve as empirically informed starting points for forecasting segment-level satisfaction responses to motivational investment; longitudinal replication is required to validate these parameters as genuine predictive instruments. Prescriptive capability follows directly from relative weight decomposition, translating effect sizes into an evidence-ordered intervention sequence. Section 6 operationalizes this progression.

Ethical Risk Matrix: People Analytics In Society 5.0 Manufacturing Contexts

Society 5.0's human-centred values require that analytics capability serves worker flourishing rather than organizational efficiency at workers' expense. Table 2 presents an ethical risk matrix identifying the specific risks each people analytics application creates in Nigerian manufacturing contexts, the severity of those risks, and the human-centred safeguards required.

Table 2 Ethical Risk Matrix for Demographic People Analytics in Nigerian Manufacturing OrganizationsSociety 5.0 Human-Centred Safeguards

PA Application	Ethical Risk	Risk Level	Human-Centred Safeguard
Occupational grade segmentation of satisfaction data	Stereotyping — grade-level averages treated as individual prescriptions	Moderate	Grade data informs strategy design, not individual decisions; individual consent and anonymity preserved; results shared in aggregate only
Qualification–fit identification (overqualification flagging among production workers)	Labelling — overqualified workers face adverse treatment or exclusion	High	Overqualification data used exclusively to trigger role enrichment and internal mobility pathways; never used in disciplinary, selection, or termination decisions; results shared only in aggregate
Predictive satisfaction scoring by demographic group	Algorithmic discrimination — automated decisions disadvantaging protected groups	High	Human review mandatory for all prescriptive outputs; demographic variables prohibited from compensation or promotion algorithms; quarterly transparency reports to workforce representatives
Production floor sentiment monitoring	Surveillance — erosion of psychological safety; conflation with performance monitoring	High	Participation strictly voluntary; data aggregated to section/shift minimum; no linkage to production performance metrics; union or worker representative consultation required before implementation

Evidence-informed budget allocation using relative weight rankings	Distributional inequity — investment concentrated at higher-grade segments despite evidence pointing to production worker deficits	Moderate	Intervention priority sequence (working conditions, recognition, compensation equity) explicitly directs resources toward segments with largest demonstrated motivational gaps; equity audit required before budget allocation; minimum investment floor for non-skilled grade mandated

Note. Risk levels: High = potential for direct individual harm or systemic discrimination; Moderate = potential for indirect harm if safeguards are absent. All applications require explicit employee communication, informed consent for data collection, and—for High-risk applications in manufacturing—worker representative consultation prior to deployment.

Four principles govern the ethical framework underlying Table 2, drawn from the intersection of Society 5.0 values and Nigerian industrial justice research.

The transparency principle requires that manufacturing workers understand what data is collected, how it is analysed, and how analytics outputs influence HR decisions affecting them. In Nigerian manufacturing environments where organizational policy scored the lowest motivational factor (M = 2.76), transparency is not merely an ethical aspiration but an organizational trust requirement. Analytics processes perceived as opaque or management-serving will erode the workforce confidence on which the entire analytics value proposition depends, producing a counterproductive feedback loop in which the intervention designed to improve conditions becomes itself a source of dissatisfaction.

The fairness principle requires that analytics outputs be used to reduce rather than reproduce existing workforce inequalities. The empirical evidence shows that non-skilled production workers, early-career employees, and educationally underemployed graduates carry disproportionate satisfaction deficits. People analytics should direct organizational investment toward these groups—not toward protecting high performers at senior grades while deprioritizing those with the greatest motivational need.

The individuality principle requires that grade-level analytics findings never substitute for individual-level human judgment in personnel decisions. The statistical patterns described in this study describe tendencies across occupational groups; they describe no individual worker’s experience. Grade variables may inform strategy design but must not be used as automated inputs to individual employees’ compensation, promotion, or employment continuity.

The proportionality principle requires that the invasiveness of data collection be proportionate to the benefit it enables. This principle is especially critical in manufacturing environments where the existing infrastructure of quality control, time-and-motion, and attendance monitoring already subjects workers to data collection that is often experienced as disciplinary rather than supportive. Survey-based people analytics represents a low-invasiveness, high-intelligence alternative that avoids the surveillance dynamic.

Implementation Roadmap For Nigerian Manufacturing Organizations

Table 3 presents a phased implementation roadmap translating the people analytics maturity model into specific, sequenced actions for Nigerian manufacturing HR functions. The roadmap is calibrated to the resource realities of Nigeria’s industrial sector—acknowledging that most manufacturing HR departments lack data science capability, advanced analytics software, or dedicated people analytics teams—while maintaining fidelity to the human-centred principles that distinguish Society 5.0-aligned HRM from efficiency-first surveillance.

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Table 3 Phased People Analytics Implementation Roadmap for Nigerian Manufacturing HRM with Society 5.0 Scope Alignment

Phase	PA Capability	HRM Action	Human-Centred Outcome	Scope Points
Phase 1 (0–6 months)	Descriptive analytics: occupational grade profiling; satisfaction baseline by section and shift	Administer validated motivation–satisfaction survey segmented by grade, tenure, gender, and qualification fit; establish working conditions and compensation benchmarks by facility	Plant management understands where satisfaction gaps exist across the occupational hierarchy and which conditions are worst-rated at production worker grade	4, 8
Phase 2 (6–18 months)	Diagnostic analytics: moderation analysis; factor sensitivity mapping by grade and tenure segment	Use relative weight rankings and moderation slopes to identify priority interventions by segment; deploy working conditions improvement, recognition schemes, and compensation equity review in sequence ordered by demonstrated effect size; initiate role enrichment for educationally underemployed graduates	HRM moves from uniform to differentiated strategy; highest-effect-size interventions deployed to highest-gap segments (production workers) first, ordered by demonstrated relative weight	4, 5, 8, 9
Phase 3 (18–36 months)	Predictive analytics: satisfaction trajectory modelling; turnover risk scoring by occupational segment	Integrate satisfaction data into talent management; create early-warning dashboards by shift and section; evaluate intervention effectiveness by segment; incorporate into HR budgeting	HR becomes data-informed strategic partner; Society 5.0 human-centred values embedded in workforce decisions with full ethical audit trail and worker representative transparency	5, 9, 10

Note. Scope Points refer to journal scope categories most directly addressed: 4 = Current workforce trends; 5 = HR in Society 5.0; 8 = New methodologies; 9 = Expected HR transformations; 10 = Data science and ethics. All phases require parallel development of the ethical governance framework in Table 2 and, for Phase 3, worker representative consultation.

Phase 1 — Descriptive Foundation (0–6 Months)

The starting point for Nigerian manufacturing organizations' people analytics journey is systematic measurement calibrated to the occupational granularity of industrial work. Most Nigerian manufacturing HR surveys—where they exist at all—ask aggregate satisfaction questions that collapse the substantial heterogeneity between production workers, semi-skilled operatives, technical staff, and management into a single meaningless mean. The validated instruments deployed in this study (adapted MSQ, JDI, and motivation subscales capturing working conditions, recognition, and compensation equity dimensions) provide the measurement template that Phase 1 requires. Organizations can implement this instrument with minimal adaptation: it requires no specialist software, is administrable during shift changeovers, and produces the occupationally segmented satisfaction profile that descriptive analytics demands.

Phase 1's analytical outputs—satisfaction means by occupational grade and tenure cohort, motivational factor rankings within the manufacturing workforce—are achievable with SPSS, Excel, or Google Sheets and standard descriptive statistics. What Phase 1 requires is HR leadership commitment to making data collection systematic, representative across production shifts and sections (not merely among administrative staff), and ethically governed. The single most common failure mode in Nigerian manufacturing HR survey practices is surveying office-based employees while treating factory floor workers' satisfaction as either unknowable or irrelevant—which produces descriptive analytics that reflects the least analytically important segment of the workforce.

Phase 2 — Diagnostic Intelligence (6–18 Months)

Phase 2 advances from knowing what the satisfaction landscape looks like to understanding why it looks that way and for whom motivational investments produce the greatest returns. This requires moderation analysis capability—testing whether the relationship between working conditions improvements, recognition programs, or compensation equity interventions and satisfaction outcomes differs across occupational segments. Both are achievable with SPSS PROCESS macro (Hayes, 2018) or R.

The specific diagnostic outputs Phase 2 produces include: a ranked motivational factor profile for each major occupational segment (by grade, career stage, qualification–fit status); relative weight comparisons revealing which factors have the strongest demonstrated influence on satisfaction for which segments; moderation slopes identifying where motivational investment produces the largest returns; and the identification of segments carrying disproportionate satisfaction deficits—particularly non-skilled production workers, early-career employees, and educationally underemployed graduates—whose motivational needs most urgently require organizational response. Phase 2 is where people analytics transitions from a reporting function to a strategic manufacturing HR capability.

Phase 3 — Predictive and Strategic Integration (18–36 Months)

Phase 3 applies the provisional predictive parameters established in Phase 2 to real-time workforce monitoring. The moderation slopes documented in this study—demonstrating, for example, that long-tenure employees' satisfaction is more sensitive to working conditions deterioration (B = 0.61) than new entrants' (B = 0.42)—provide the best empirically grounded starting parameters currently available for Nigerian manufacturing analytics. These slopes are cross-sectional and require longitudinal replication to function as validated predictive instruments; Phase 3 is precisely when that replication occurs. Extending to longitudinal data collection at regular intervals using the Phase 1 instrument allows within-person and within-section change analysis that converts cross-sectional differential parameters into tracked trajectory models—moving from proof-of-concept to genuine predictive analytics capability.

Phase 3 is also where people analytics becomes genuinely integrated into strategic manufacturing HR decision-making: linking satisfaction data to quality and safety performance metrics, connecting motivational investment tracking to outcome measurement, and incorporating analytics outputs into HR budgeting processes. At this stage, the manufacturing HR function has transformed from an administrative unit that manages personnel processes to a strategic partner that produces workforce intelligence—the Society 5.0 vision of human-centred organizational capability applied to the industrial context that arguably needs it most.

DISCUSSION AND THEORETICAL IMPLICATIONS

Repositioning Classical Research Within the Analytics Pipeline

The core argument of this article—that motivation–satisfaction research in manufacturing is most valuable when understood as input to a people analytics pipeline rather than as an end in itself—has implications for how the organizational behaviour field understands its practical relevance to industrial contexts. A definitional clarification is warranted here. People analytics in its mature, enterprise form involves large-N administrative datasets, proprietary HR system integration, and continuously updated predictive models—capabilities substantially beyond what the present study deploys. What this article demonstrates is a methodologically accessible proof-of-concept: that cross-sectional survey data, designed with occupational granularity and analysed with moderation techniques available in standard statistical packages, can be mapped onto each level of the analytics maturity model. The study does not claim to constitute predictive analytics in the full longitudinal sense; it claims to generate the empirically grounded parameters—differential slopes, relative weights, segment-level satisfaction profiles—that a longitudinal predictive analytics capability would require as its starting point. This distinction is important for both scientific integrity and practical uptake: Nigerian manufacturing HR functions should understand the present framework as a Phase 1–2 foundation, not as a substitute for the longitudinal data collection that genuine predictive capability demands.

Future motivation–satisfaction research oriented toward manufacturing people analytics application should prioritize: occupational granularity sufficient to enable grade-level analysis; longitudinal measurement enabling trajectory modelling by shift and section; and factor sensitivity analysis by tenure and career stage rather than merely main effect reporting. The present study's moderation analysis is directly relevant to the predictive analytics level in a way that main effect studies are not, because differential slopes enable differential prediction rather than merely differential description.

People Analytics in Nigerian Manufacturing: Developing Economy Context

The HR analytics literature has concentrated almost exclusively in Western organizational contexts where data infrastructure, analytical capability, and privacy regulation are substantially more developed than in sub-Saharan Africa. The Ethiopian HR analytics study (Habtamu et al., 2025) finding that HR analytics significantly enhances organizational performance through strategic alignment confirms that the analytics value proposition holds in developing economy contexts. The present article extends this by specifying what analytics capability looks like at each maturity level for Nigerian manufacturing, how it can be implemented with existing resources, and what ethical constraints are specifically salient in high-power-distance, physically hazardous industrial environments.

The Nigerian manufacturing context differs from both Western manufacturing and Nigerian service sector contexts in ways that shape implementation priorities and ethical requirements. Factory floor data collection faces the challenge of shift patterns and literacy variation among production workers that are irrelevant in office contexts. Power asymmetries between HR functions and production management are acute, meaning analytics outputs must be presented in forms that non-technical plant management can understand and act on. And the existing infrastructure of production monitoring creates a surveillance backdrop against which any new data initiative will be interpreted—making the transparency and consent framework not a procedural formality but a substantive precondition for analytics legitimacy.

Contribution to Society 5.0 HRM Theory

This article's theoretical contribution to Society 5.0 HRM in manufacturing is the specification of what human-centred analytics means in practice within an industrial context—not as an abstract value but as a concrete set of design choices about what data is collected, how it is analysed, for what purposes it is used, and what governance structures ensure it serves worker flourishing rather than organizational surveillance. The four principles articulated in Section 5 (transparency, fairness, individuality, proportionality) constitute the beginning of a Society 5.0-aligned analytics governance framework calibrated to Nigerian manufacturing's specific power dynamics and structural inequalities.

The fairness principle deserves particular emphasis in the manufacturing context. The finding that non-skilled production workers carry a satisfaction deficit of 0.40 points relative to supervisory staff—while receiving fewer organizational motivational investments in recognition, development, and advancement—creates a distributional equity challenge that Society 5.0 values demand be addressed explicitly. People analytics that directs investment toward highest-gap segments rather than highest-performance or most-visible segments operationalizes the equity commitment in HRM resource allocation terms. This constitutes a novel prescriptive contribution specifically salient for Nigerian manufacturing: the specification of how analytics-informed resource allocation can deliver equity for the workers who most need it and least have the organizational power to advocate for it themselves.

CONCLUSION

Nigerian manufacturing HRM stands at a methodological inflection point. The instinct-driven, uniform-strategy approaches that characterize most current practice are not merely inefficient—they are inequitable, systematically under-serving production workers, early-career employees, and educationally underemployed graduates who carry the greatest motivational deficits while receiving the least organizational motivational investment. People analytics provides the intelligence infrastructure to move from this intuition-based uniformity to evidence-based differentiation: knowing that production workers need working conditions improvement and meaningful recognition most urgently, that underemployed graduates need role enrichment rather than higher pay, that long-tenure employees carry the strongest motivation–satisfaction coupling—and deploying organizational resources accordingly.

The transition from instinct to intelligence in Nigerian manufacturing does not require advanced AI, big data infrastructure, or dedicated analytics teams at its early stages. It requires measurement rigor (including factory floor workers, not just administrative staff), analytical capability (moderation analysis applied to existing survey data), and the organizational commitment to let evidence inform resource allocation decisions that tradition and hierarchy would prefer to make on intuitive grounds. The phased implementation roadmap presented here provides Nigerian manufacturing HR functions with a realistic path from where most currently stand—collecting little or no motivational data from production workers—to where Society 5.0's human-centred HRM vision requires them to reach: deploying workforce intelligence in service of every employee's flourishing, including those at the most physically demanding and least analytically visible positions on the factory floor.

The ethical risk matrix is not a caveat to be appended to the analytics enthusiasm—it is a constitutive part of the people analytics proposition for manufacturing. Analytics capability not governed by transparency, fairness, individuality, and proportionality principles will reproduce in data form the structural inequalities it was supposed to address, and will do so with the additional legitimacy that algorithmic outputs are often accorded over human judgment. In Nigerian manufacturing contexts where those inequalities are empirically documented and their motivational consequences measurable, the ethical framework is not optional. It is what distinguishes Society 5.0-aligned industrial HRM from production-efficiency surveillance dressed in HR language.

Future research should evaluate the effectiveness of the phased implementation roadmap through longitudinal case study designs tracking Nigerian manufacturing organizations through analytics maturity stages, assess whether people analytics-informed HRM produces measurable satisfaction improvements relative to uniform-strategy comparators, and examine how worker representative consultation models in unionised manufacturing environments can be incorporated into analytics governance frameworks to strengthen the legitimacy—and therefore the impact—of people analytics as a tool for worker flourishing rather than organizational control.

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Contact address:

Yusuf Sunday Onuminya, Faculty of Management Science,

Ahmadu Bello University, Zaria, Nigeria,

Dr. Mohammed Ibrahim Aminu, Faculty of Management

Science, Ahmadu Bello University, Zaria, Nigeria, email:

Okpara Christopher Chinedu, Faculty of Management Science, University of Jos, Nigeria,

Akinrinlola Florence Nkonye, Faculty of Management Science, University of Jos, Nigeria,

Akogwu Paul Shaibu, Ahmadu Bello University, Zaria, Nigeria

Haladu Mohammed Aliyu, Ahmadu Bello University, Zaria, Nigeria

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