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From Candidate Sourcing to Successful Placement: A Data-Driven Model for Matching Software Talent with Enterprise Skill Requirements

[1] Rasheed Akhigbe, [2] Miracle Wikiri, [3] Chioma Ann Udeh
[1] Independent Researcher, Ontario, Canada
[2] Independent Researcher, Nashville, Tennessee, United States of America
[3] Independent Researcher, Lagos, Nigeria

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Corresponding Author: **Rasheed Akhigbe**

Abstract
Background: The loss of information and fit across sourcing, assessment, matching, selection, and placement limits better match quality, shorter time-to-supply, and stronger placement durability.
Purpose: This conceptual review integrates research and institutional guidance published to date to explain the problem and develop an actionable framework for enterprise software staffing and digital talent platforms.
Method: The paper uses an integrative review organized around demand definition, evidence, interaction, decisions, transition, and feedback.
Results: The synthesis identifies six recurring requirements: Clear demand signals, job-relevant evidence, accessible communication, multidimensional matching, transition support, and governed learning. It proposes a five-stage model comprising Demand specification, structured evidence capture, Multidimensional matching, Human validation, Post-placement learning. The model pairs each stage with controls and measures, including demand stability, evidence quality, conversion, time to contribution, sustained performance, and fairness indicators.
Conclusion: Data-driven software talent matching should be managed as a connected socio-technical system. Organizations should pilot the model in a bounded role family, compare outcomes with a baseline, examine unequal effects, and revise the process before scaling.

Keywords: Data-Driven Software Talent Matching, Workforce Systems, Talent Pipelines, Skills Assessment, Organizational Performance, Responsible Technology

1. Introduction

Organizations increasingly depend on specialized knowledge, digital coordination, and credible workforce information. Yet organizations continue to face the loss of information and fit across sourcing, assessment, matching, selection, and placement. This gap matters because access to people is not equivalent to access to productive capability. Employers must define work, recognize evidence, compare candidates, support entry into a role, and learn from outcomes. Each transition creates information loss and avoidable exclusion. Research on changing work emphasizes the interaction between technology, skills, institutions, and worker opportunity (Black & van Esch, 2020; World Economic Forum, 2023; Tonoyan *et al*., 2022; Dosunmu & Ogundele, 2019; Melão & Reis, 2021).

This paper examines Data-driven software talent matching in the setting of enterprise software staffing and digital talent platforms. Its central argument is that isolated recruitment actions produce unstable results. A coherent operating system must connect demand information, assessment, communication, decisions, onboarding, performance, and feedback. The intended result is better match quality, shorter time-to-supply, and stronger placement durability. The paper treats workforce systems as socio-technical arrangements. Technology structures information and scale, while people supply interpretation, accountability, trust, and contextual judgment (Akomolafe & Agu, 2018; Aifuwa *et al*., 2020; Annan, 2022; Dosunmu & Ogundele, 2019; Siow & Mak, 2017).

The contribution is a practice-oriented conceptual framework derived from interdisciplinary literature. The framework does not promise automatic solutions. It specifies decision points, information flows, controls, and outcome measures that organizations may test in real settings. The analysis also separates activity measures, such as messages sent or candidates submitted, from outcome measures, such as verified capability, successful entry, sustained performance, and fair access. In this analysis, the claim is assessed through match quality, adverse impact, explainability, and post-hire performance.

Three questions guide the analysis: (1) Where does match quality deteriorate across the staffing pipeline? (2) Which data elements support a defensible representation of skill and role demand? (3) How should algorithmic matching and human judgment interact?

2. Background and theoretical foundations

Human capital acquires organizational value when knowledge and skill combine with appropriate work design, coordination, and opportunity. Staffing research therefore extends beyond attraction and selection. It considers how firms recognize capability, how applicants interpret signals, and how selection decisions affect later performance (Köchling & Wehner, 2020; Raghavan *et al*., 2020). For enterprise software staffing and digital talent platforms, distance and rapid skill change make these problems more pronounced (Lawal & Oduleye, 2018; Annan, 2022; Falemi *et al*., 2020; Downes *et al*., 2023).

Signaling theory helps explain why employers and workers struggle to evaluate each other under uncertainty. Degrees, job titles, portfolios, assessments, referrals, and prior projects serve as signals, but their meaning differs across countries, firms, and occupations. A useful system triangulates signals instead of treating one proxy as proof. Structured evidence reduces ambiguity when it links a claimed capability to a task, an observable work product, a level of complexity, and a recent context of use (Sanni & Atima, 2021).

A systems perspective adds a second insight. Local optimization can damage the full pipeline. Increasing applicant volume may overload assessment teams. Tightening filters may improve apparent efficiency while excluding unconventional talent. Accelerating placement may transfer unresolved role ambiguity to onboarding. The relevant unit of analysis is the complete pathway from demand formation to productive participation and continued learning (Filani *et al*., 2022; Tonoyan *et al*., 2022; Lawal & Oduleye, 2019; Airiau *et al*., 2023).

Service quality and procedural justice add a third insight. People judge systems through accuracy, timeliness, clarity, consistency, and the opportunity to correct errors. These qualities influence trust and continued participation. A workforce platform or employer therefore needs both operational efficiency and a defensible process. Transparency about stages, evidence requirements, decision ownership, and response timing is part of system performance rather than an optional communication layer (Akhigbe *et al*., 2023).

2.1 Extended evidence base and research gap

Human capital and strategic value. Workforce capability produces value through knowledge, deployment, complementary systems, and opportunity. Strategic human-resource research links selection and development to organizational performance, while resource-based and knowledge-based theories explain why scarce capability must be organized rather than merely acquired. (Aguinis, 2013; Ajzen, 1991; Allen, 2006; Appelbaum *et al*., 2000; Armstrong & Taylor, 2017; Arthur *et al*., 2003; Bangerter *et al*., 2012; Barber, 1998).

Recruitment signals and attraction. Recruitment is an exchange of signals under uncertainty. Applicants interpret employer information, process quality, and role realism, while employers infer capability from incomplete evidence. Clear requirements, credible communication, and structured evidence improve mutual understanding and reduce avoidable withdrawal. (Barney, 1991; Bauer, 2010; Becker, 1993; Bondarouk & Ruël, 2009; Borman & Motowidlo, 1997; Cable & Turban, 2001; Campion *et al*., 1997; Cappelli, 2001). In this analysis, the claim is assessed through match quality, adverse impact, explainability, and post-hire performance.

Selection validity and procedural quality. Selection methods differ in reliability, validity, accessibility, cost, and participant response. Structured interviews, job-relevant work samples, and validated procedures strengthen consistency. Procedural quality also matters because participant reactions influence acceptance, reputation, and continued engagement. (Cappelli & Keller, 2014; Chapman *et al*., 2005; Cohen & Levinthal, 1990; Coleman, 1988; Collins & Smith, 2006; Davis, 1989; Delery & Doty, 1996; Dineen & Soltis, 2011; Tonoyan *et al*., 2022; Anene & Clement, 2022).

Learning, socialization, and deployment. Selection does not complete capability formation. Training design, onboarding, role clarity, team support, psychological safety, and work design shape whether knowledge becomes effective performance. Early outcomes therefore reflect both individual preparation and the environment into which a person enters. (Edmondson, 1999; Gatewood *et al*., 2016; Goldin & Katz, 2008; Granovetter, 1973; Grant, 1996; Hackman & Oldham, 1976; Hausknecht *et al*., 2004; Huselid, 1995). Within enterprise recruitment systems, its main boundary conditions are data quality, model governance, occupational change, and human oversight.

Technology adoption and digital HR. Digital workforce systems change the speed and scale of information processing, yet user acceptance, process fit, data quality, and governance determine results. Technology should support a defined decision process. Weak definitions transferred into software create faster inconsistency rather than dependable improvement. (International Organization for Standardization, 2016; Jiang *et al*., 2012; Kalleberg, 2009; Kavanagh & Johnson, 2018; Klein & Polin, 2012; Kozlowski & Ilgen, 2006; Kristof, 1996; Lepak & Snell, 1999; Ilodigwe & Adesemoye, 2021; Annan, 2022; Lawal & Oduleye, 2019; Lawal & Oduleye, 2023).

Networks and access to opportunity. Professional and organizational networks transmit information, referrals, credibility, and learning. Network design influences who becomes visible and which opportunities circulate. Digital platforms extend reach, while persistent differences in access, trust, and signal interpretation require deliberate inclusion and transparent rules. (Levashina *et al*., 2014; Lievens, 2007; March, 1991; Marler & Boudreau, 2017; Morgeson & Humphrey, 2006; Noe, 2017; Nonaka, 1994; Organisation for Economic Co-operation and Development, 2016; Annan, 2022; Rukh *et al*., 2023).

Analytics, measurement, and organizational learning. Analytics becomes useful when measures connect to decisions and later outcomes. Organizations should combine operational indicators with quality, experience, and fairness measures. Feedback loops support correction when leaders preserve definitions, examine exceptions, and distinguish correlation from causal evidence. (Phillips & Gully, 2015; Rogers, 2003; Rynes & Barber, 1990; Saks, 2006; Salas *et* *al*., 2012; Schmidt & Hunter, 1998; Spence, 1973; Stone *et al*., 2015; Ilodigwe & Adesemoye, 2021; Mayo *et al*., 2021; Akhigbe *et al*., 2023; Saxena *et al*., 2020).

Integrated workforce-system design. The literature supports an integrated view of demand, evidence, matching, transition, and learning. No isolated intervention addresses every failure point. Coherent systems align task definitions, assessment, communication, technology, manager behavior, participant support, and performance review around a shared outcome. (Strohmeier, 2007; Teece *et al*., 1997; Venkatesh *et al*., 2003; Wanberg, 2012; Wright & McMahan, 1992; Filani *et al*., 2022).

3. Methodology

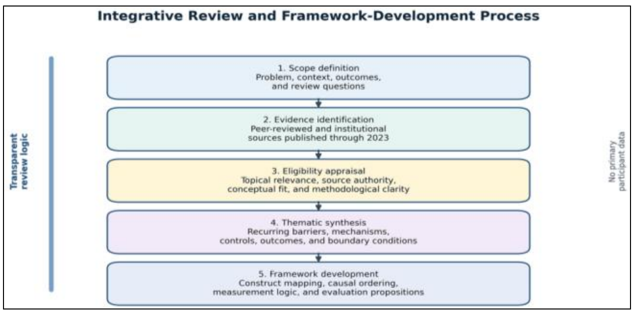
The study uses an integrative conceptual review. Sources published through December 2023 were eligible. The review focused on peer-reviewed research, books, standards, and reports from recognized public or professional institutions. Search concepts combined terms related to Data-driven software talent matching, workforce systems, recruitment, skills, platforms, performance, fairness, digital work, and organizational outcomes (Annan, 2022).

Sources were interpreted through four questions: What problem does the source define? What mechanism links an intervention to an outcome? What assumptions limit transfer across settings? Which measure would indicate success or harm? This approach supports theory integration without presenting the review as a statistical meta-analysis. It also reduces the risk of converting broad associations into unsupported causal claims (Lawal & Oduleye, 2019).

The synthesis followed three stages. First, concepts were grouped into demand, evidence, interaction, decision, transition, and feedback domains. Second, recurring breakdowns were mapped across the workforce pathway. Third, design principles were translated into a staged framework. The framework represents an analytical proposition for future testing, not an empirical finding from primary data (Lawal & Oduleye, 2019; Fadayomi *et al*., 2019).

The review has boundaries. English-language material is emphasized. Fast-changing practices may advance faster than peer-reviewed publication. Institutional reports offer timely evidence but differ in method and scope. The paper addresses organizational design and does not replace jurisdiction-specific legal advice, professional licensing rules, collective agreements, or immigration requirements. Within enterprise recruitment systems, its main boundary conditions are data quality, model governance, occupational change, and human oversight.

Fig 1 summarizes the integrative review and framework-development process.



Source: Authors' conceptualization

Fig 1: Integrative review and framework-development process

4. Findings and thematic synthesis

Theme 1: Demand clarity. Weak outcomes often begin before sourcing. Employers describe technologies rather than work, combine unrelated skills, or fail to distinguish essential capabilities from preferences. The result is a moving target. For Data-driven software talent matching, demand should be expressed through tasks, expected outputs, operating constraints, collaboration needs, proficiency levels, and acceptable learning time. Clear demand improves search, assessment, expectation setting, and post-entry evaluation (Yeboah *et al*., 2022; Filani *et al*., 2022).

Theme 2: Evidence quality. Résumés remain useful summaries, but they compress context and often rely on inconsistent labels. Stronger evidence combines structured career information with work samples, task-based assessments, verified credentials, references, and discussion of reasoning. Evidence should remain proportionate to the role. Excessive testing creates burden and may select for test familiarity rather than job performance. Validation, accessibility, privacy, and adverse-impact review remain central concerns. For data-driven software talent matching, implementation fidelity determines whether this mechanism operates as proposed.

Theme 3: Communication and participation. Candidate and partner behavior responds to message relevance, channel accessibility, timing, trust, and visible progress. Generic outreach treats attention as unlimited. Effective engagement explains why an opportunity fits, what action is required, how long the process takes, and what follows. Multichannel communication works best as coordinated choice rather than repeated pressure. Consent, frequency controls, language, time zones, and disability access shape responsible engagement. The paper therefore connects this claim directly to match quality, adverse impact, explainability, and post-hire performance.

Theme 4: Matching as a multidimensional decision. Keyword overlap captures only part of fit. Matching also involves skill depth, recency, domain knowledge, problem complexity, availability, communication, location constraints, compensation, security requirements, and development potential. A model should expose these dimensions to reviewers. A single opaque score hides tradeoffs and encourages false precision. Human review should test the model's assumptions and document exceptions. Empirical tests should report variation in data quality, model governance, occupational change, and human oversight.

Theme 5: Transition and deployment. Acceptance is an intermediate outcome. Productive participation depends on access, role clarity, tools, documentation, relationships, feedback, and realistic early assignments. Weak onboarding makes a sound selection appear unsuccessful. Organizations should track time to first meaningful contribution, early support needs, manager readiness, worker experience, and ninety-day role stability alongside hiring speed (Risavy & Hausdorf, 2011).

Theme 6: Learning and governance. Systems improve when outcome data returns to earlier stages. Rejection reasons should refine sourcing. Assessment results should refine demand definitions. Early performance should test the validity of selection evidence. Complaints and disparate outcomes should trigger review. Governance requires data ownership, access controls, retention rules, documented decision authority, appeal routes, and periodic evaluation of automated tools (Ahiaeke Patrick *et al*., 2021; Aneke *et al*., 2023; Mbonu *et al*., 2022; Ilodigwe & Adesemoye, 2021).

Taken together, the literature suggests that the loss of information and fit across sourcing, assessment, matching, selection, and placement is rarely solved by adding one technology or one sourcing channel. The more durable response connects organizational choices across the full pathway. This interpretation is consistent with institutional accounts that link workforce outcomes to both capability formation and the rules governing access to opportunity (U.S. Equal Employment Opportunity Commission, 2023; World Economic Forum, 2023; Dosunmu & Ogundele, 2019).

5. Proposed conceptual framework

The proposed framework contains five connected stages: Demand specification, Structured evidence capture, Multidimensional matching, Human validation, Post-placement learning. Each stage has an operational purpose, a required evidence set, and a feedback relationship with the others. The sequence provides discipline, but implementation should remain iterative. New information at a later stage may require the organization to revise an earlier assumption.

Stage 1, Demand specification, defines the unit of demand. Teams identify the business or public-service objective, tasks, outputs, timing, constraints, and consequence of delay. They separate current requirements from trainable gaps. The main control is an approved demand brief owned jointly by operational and workforce leaders. Suggested measures include demand stability, clarification cycles, forecast accuracy, and the percentage of requirements tied to observable work (Akin-Oluyomi *et al*., 2023; Aifuwa *et al*., 2020).

Stage 2, Structured evidence capture, creates a structured representation of capability and supply. The organization specifies acceptable forms of evidence and checks their relevance, recency, and level. It records uncertainty instead of converting missing information into a negative judgment. Suggested measures include evidence completeness, assessment reliability, accessibility, candidate burden, and differences in progression rates across relevant groups (Dosunmu & Ogundele, 2019; Filani *et al*., 2022).

Stage 3, Multidimensional matching, connects demand and supply through explainable rules and accountable review. Screening criteria should map to the approved demand brief. Reviewers examine both strong matches and selected near matches to detect overly narrow rules. Suggested measures include qualified slate rate, precision of recommendations, time in stage, override patterns, and the stated reasons for advancement or rejection (Aifuwa *et al*., 2020).

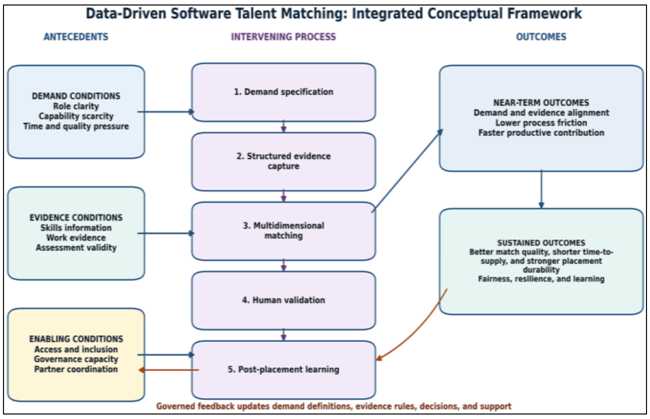
Stage 4, Human validation, supports movement from selection to productive participation. Responsibilities, access, communication, learning resources, and checkpoints are prepared before entry. The organization identifies which gaps require training and which indicate an incorrect match. Suggested measures include offer or participation conversion, time to access, time to first meaningful contribution, early issue resolution, and participant experience (Tonoyan *et al*., 2022).

Stage 5, Post-placement learning, converts outcomes into system learning. Teams compare forecasts with actual performance, examine departures and complaints, review partner results, and revise definitions or controls. Learning meetings should distinguish individual cases from recurring patterns. Suggested measures include sustained success, quality, stakeholder satisfaction, rework, retention, fairness indicators, and the number of verified improvements adopted.

The framework rests on four safeguards. First, proportionality limits data collection and assessment burden to what the decision requires. Second, explainability gives affected people and decision owners an intelligible account of criteria. Third, human accountability assigns named owners to consequential decisions. Fourth, continuous validation tests whether measures still represent job-relevant capability as technology and work change (Mbonu *et al*., 2022; Lawal & Oduleye, 2019; Lawal & Oduleye, 2023).

Implementation should begin with one role family or project category. A baseline should capture current cycle time, progression, quality, participant experience, and outcome variation. The pilot should run through at least one complete staffing and early-performance cycle. Teams should compare results with the baseline, document unintended effects, and revise the framework before scaling. This sequence supports learning without placing the entire organization under an untested design. This interpretation is specific to enterprise recruitment systems and should not be generalized without testing.

Fig 2 presents the integrated conceptual framework linking antecedents, intervening processes, and outcomes.



Source: Authors' conceptualization

Fig 2: Integrated conceptual framework linking antecedents, intervening processes, and outcomes

5.1 Framework summary

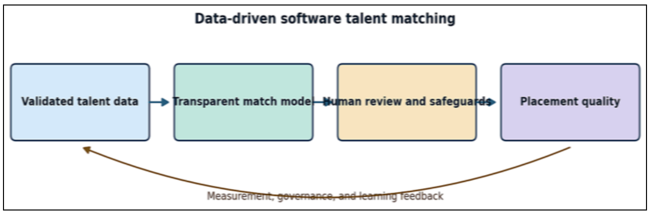
Table 1 summarizes the five-stage conceptual framework.

Table 1: Five-stage conceptual framework

Stage	Primary decision	Illustrative evidence
Demand specification	What capability is needed and why?	Approved demand brief and baseline
Structured evidence capture	What evidence represents relevant capability?	Structured profile, work evidence, assessment
Multidimensional matching	How should demand and supply be compared?	Criteria map, reviewer rationale, exceptions
Human validation	What enables productive entry?	Access checklist, learning plan, early milestones
Post-placement learning	What outcomes require correction?	Performance, experience, fairness, and correction data

The following framework translates the synthesis into a topic-specific structure for data-driven software talent matching.

Fig 3 displays the implementation and learning framework.



Source: Authors' conceptualization

Fig 3: Implementation and learning framework

Table 2 maps the evidence base to the framework constructs.

Table 2: Evidence-to-construct matrix

Construct	Evidence pattern	Role	Observable indicator
Skill representation	Structured evidence improves candidate profiles	Input	Profile completeness and validity
Match logic	Job-relevant features support fit estimation	Mechanism	Ranking accuracy and calibration
Fairness controls	Audits constrain unequal model effects	Governance	Selection-rate and error gaps
Match quality	Aligned placements support performance	Outcome	Quality, retention, and satisfaction

6. Discussion

The framework advances discussion of Data-driven software talent matching in three ways. First, it places demand quality before candidate supply. Many staffing failures attributed to a talent shortage reflect unstable requirements, unrealistic combinations of skills, or weak coordination among decision makers. Improving the demand signal changes the quantity and type of supply judged relevant (Aifuwa *et al.*, 2020; Falemi *et al.*, 2020).

Second, the framework treats matching as a governed inference rather than a mechanical ranking exercise. Data improves consistency only when definitions, measurement quality, and accountability receive equal attention. Automation may support search and comparison, while people remain responsible for context, exceptions, and consequences. This division of labor is especially important when historical decisions or incomplete data reproduce exclusion (Ilodigwe & Adesemoye, 2021; Sanni *et al.*, 2023; Wozniak, 2021).

Third, the framework extends evaluation beyond placement. A fast placement followed by delayed access, role confusion, or early departure does not represent success. Conversely, a longer process may create higher value when it resolves ambiguity and supports durable contribution. Balanced evaluation therefore combines speed, quality, experience, equity, and sustained outcomes (Ogundairo & Ayivi-Donkor, 2023).

For employers, the practical implication is to manage Data-driven software talent matching as a cross-functional capability. Business leaders own demand. Workforce teams own process design and market access. Technical experts validate evidence. Legal, security, and data leaders establish controls. Managers own deployment. Participants supply experience data. No single group holds enough information to optimize the whole system (Akhigbe *et al.*, 2023; Falemi *et al.*, 2020; Lee, 2015).

For intermediaries and partners, transparency improves coordination. Shared definitions of a qualified submission, response time, rejection reason, assessment stage, and successful outcome reduce disputes. Partner comparisons should account for role difficulty, geography, supply conditions, and small sample sizes. Measures should prompt joint problem solving rather than encourage superficial competition for volume. In this analysis, the claim is assessed through match quality, adverse impact, explainability, and post-hire performance.

For policymakers and educators, the model highlights the value of portable evidence and feedback from work into learning. Curricula and short programs become more responsive when employers describe tasks and proficiency instead of listing tools alone. Public workforce systems may support common skill language, accessible assessment, career navigation, and regional partnerships while preserving worker choice and privacy. Within enterprise recruitment systems, its main boundary conditions are data quality, model governance, occupational change, and human oversight.

The intended outcome, better match quality, shorter time-to-supply, and stronger placement durability, depends on both efficiency and legitimacy. A system that moves quickly but produces unexplained or inequitable decisions will lose participation and invite risk. A system with extensive controls but slow, duplicative stages will also fail. Responsible performance requires clear objectives, minimum necessary friction, credible evidence, and routes for correction.

6.1 Theoretical contributions and research agenda

Proposition 1: Greater demand specificity will associate with higher qualified-slate rates and lower requirement revision. This proposition should be tested with longitudinal pipeline data and controlled comparison of role briefs. Researchers should distinguish genuinely scarce skills from shortages created by compensation, location, credential inflation, or slow decisions. For data-driven software talent matching, implementation fidelity determines whether this mechanism operates as proposed.

Proposition 2: Triangulated, job-relevant evidence will predict early contribution more accurately than unstructured résumé review alone. Studies should compare work samples, structured interviews, assessments, portfolios, and prior experience while monitoring subgroup effects and participant burden. The paper therefore connects this claim directly to match quality, adverse impact, explainability, and post-hire performance.

Proposition 3: Explainable multidimensional matching with accountable human review will produce stronger trust and correction than opaque ranking. Evaluation should examine accuracy, override reasons, appeal outcomes, recruiter consistency, and worker perceptions. Experimental designs should avoid withholding necessary procedural protections. Empirical tests should report variation in data quality, model governance, occupational change, and human oversight.

Proposition 4: Integrated transition support will mediate the relationship between match quality and sustained performance. Measures should include access readiness, manager preparation, time to contribution, learning support, well-being, and role stability. This proposition recognizes that a match is enacted through organizational conditions. This interpretation is specific to enterprise recruitment systems and should not be generalized without testing.

Proposition 5: Closed-loop outcome feedback will improve system calibration over repeated cycles. Researchers should examine whether documented feedback changes demand definitions, assessment thresholds, communication, partner allocation, and onboarding. They should also test whether feedback produces convergence around valid predictors or reinforces existing preferences. In this analysis, the claim is assessed through match quality, adverse impact, explainability, and post-hire performance.

A minimum evaluation dashboard should include demand stability, time by stage, qualified conversion, assessment completion, participant withdrawal, offer acceptance, access readiness, time to contribution, quality, rework, early retention, satisfaction, subgroup progression, complaints, and correction time. Each measure requires an owner, definition, frequency, and decision rule. Metrics without a response protocol create observation without improvement. Within enterprise recruitment systems, its main boundary conditions are data quality, model governance, occupational change, and human oversight.

6.2 Managerial implications and implementation strategy

Implementation of the Demand specification, Structured evidence capture, Multidimensional matching, Human validation, Post-placement learning framework should begin with governance rather than software procurement. A named sponsor should define the operational problem, authorize access to the required data, and appoint owners from the business, workforce, technical, legal, and information-security functions. The group should agree on the unit of success. For this study, success means better match quality, shorter time-to-supply, and stronger placement durability, supported by acceptable participant experience and defensible decisions (Akhigbe *et al*., 2023; Ilodigwe & Adesemoye, 2021; Akinleye *et al*., 2023; Mbonu *et al*., 2018).

The first implementation phase is diagnosis. Teams should map the existing pathway from demand request through early performance. The map should record decision owners, inputs, outputs, systems, waiting time, rework, handoffs, and common exceptions. Interviews with hiring managers, recruiters, candidates, partners, workers, and technical reviewers should supplement process data. This mixed evidence prevents the organization from treating a reporting symptom as the root problem. For data-driven software talent matching, implementation fidelity determines whether this mechanism operates as proposed.

The second phase is definition. A data dictionary should specify every measure, including numerator, denominator, timestamp, source system, inclusion rule, owner, and review frequency. Terms such as qualified, available, submitted, accepted, deployed, successful, diverse, and retained should receive operational definitions. Without this step, teams compare different events under the same label and draw unreliable conclusions from dashboards (Atakpa & Abolaji, 2022).

The third phase is pilot design. One role family should be selected based on strategic value, sufficient activity, manageable risk, and available outcome data. The pilot should preserve a comparison baseline and document changes to criteria, communication, assessment, routing, onboarding, and review cadence. Participants should know which data are collected and how consequential decisions are made. A pilot charter should define stop conditions when harm, security concerns, or material quality decline appears (Akomolafe & Agu, 2018; Dosunmu & Ogundele, 2019; Mbonu *et al*., 2022; Ilodigwe & Adesemoye, 2021; Tübbicke, 2023).

The fourth phase is controlled operation. Weekly review should address process signals such as waiting time, missing information, withdrawal, and exceptions. Monthly review should examine outcomes such as quality, contribution, satisfaction, and unequal progression. Teams should resist daily threshold changes based on small samples. A documented change log should link each adjustment to evidence, an owner, an expected effect, and a later evaluation date. The paper therefore connects this claim directly to match quality, adverse impact, explainability, and post-hire performance.

The fifth phase is scale assessment. Expansion is appropriate only when the pilot produces stable definitions, acceptable data quality, improved target outcomes, no unresolved material harm, and clear operating ownership. Scaling should proceed by adjacent role families or business units. Each expansion requires local validation because a measure that represents capability in one context may lose meaning when tasks, stakes, technologies, or labor markets differ (Mbonu *et al*., 2022; Ilodigwe & Adesemoye, 2021).

For enterprise software staffing and digital talent platforms, partnership design deserves special attention. External suppliers, educators, platforms, and community organizations should receive clear demand information and structured feedback. Contracts or operating agreements should define data access, response timing, candidate ownership, assessment reuse, dispute handling, privacy, and performance review. Partnership governance should reward truthful information and durable outcomes rather than candidate volume alone (Annan, 2022; Mbonu *et al*., 2022; Ilodigwe & Adesemoye, 2021).

Change management should address the daily decisions of affected groups. Managers need support to write task-based requirements and interpret evidence. Recruiters need guidance on structured review and candidate communication. Technical experts need calibrated evaluation rubrics. Participants need clear instructions and correction routes. Leaders need dashboards that show tradeoffs instead of a single headline number. Training should use real cases, supervised practice, and follow-up review rather than one-time presentations. Empirical tests should report variation in data quality, model governance, occupational change, and human oversight.

Resource planning should cover people, time, data engineering, assessment development, accessibility, security, legal review, participant support, and evaluation. Small organizations may begin with a spreadsheet, agreed definitions, structured templates, and a recurring review meeting. Large organizations may integrate applicant tracking, talent marketplaces, learning systems, identity tools, and project platforms. The maturity of technology should follow the maturity of the operating model (Ahiaeke Patrick *et al*., 2021; Mbonu *et al*., 2022; Ahmed & Odejobi, 2018).

A twelve-month roadmap offers a practical sequence. Months one and two establish governance and baseline measures. Months three and four map demand and evidence. Months five and six redesign communication and matching rules. Months seven through nine operate the pilot and collect early outcome data. Months ten and eleven test adjustments and review fairness. Month twelve determines whether to scale, revise, or stop. Timelines should change when risk, volume, or legal review requires more evidence (Mbonu *et al*., 2018; Ilodigwe & Adesemoye, 2021).

6.3 Policy, societal, and governance implications

Workforce systems allocate opportunity and shape organizational capacity. Their risks therefore extend beyond technical error. A system may exclude qualified people through inaccessible assessments, stale skill taxonomies, geographic proxies, language assumptions, inconsistent reviewer behavior, or unexamined historical data. It may also expose confidential business information or personal data. Risk management should begin with the purpose and consequence of each decision (Akhigbe *et al*., 2023). For data-driven software talent matching, implementation fidelity determines whether this mechanism operates as proposed.

Job relevance is the first control. Every criterion should connect to an essential task, operating condition, or defensible organizational need. Teams should remove criteria retained only through habit. They should distinguish between capability required on entry and capability suitable for supported learning. This distinction expands the feasible talent pool while preserving performance expectations. This interpretation is specific to enterprise recruitment systems and should not be generalized without testing.

Data minimization is the second control. Organizations should collect information needed for a defined decision and retain it for a stated period. Access should follow role requirements. Sensitive or proxy variables require heightened review. Participants should receive a plain-language explanation of collection, use, sharing, correction, and retention. Security controls should extend to partners and assessment vendors (Dosunmu & Ogundele, 2019; Mbonu *et al*., 2022).

Fairness assessment is the third control. Overall accuracy does not reveal whether errors concentrate among particular groups. Teams should examine progression, false exclusion, assessment completion, withdrawal, override, and outcome quality where lawful and feasible. Quantitative differences require contextual investigation rather than automatic assumptions about cause. Qualitative feedback helps reveal access barriers or confusing requirements hidden by aggregate measures. In this analysis, the claim is assessed through match quality, adverse impact, explainability, and post-hire performance.

Explainability and contestability form the fourth control. Affected people should receive meaningful information about process stages and job-related reasons. Reviewers should see which evidence influenced a recommendation and where uncertainty exists. A correction route should address inaccurate records, technical failures, duplicated profiles, assessment interruptions, and inconsistent decisions. High-impact decisions require human ownership and documented review. Within enterprise recruitment systems, its main boundary conditions are data quality, model governance, occupational change, and human oversight.

Vendor governance is the fifth control. Marketing claims about artificial intelligence, matching, or assessment should be tested against documented methods and relevant outcomes. Contracts should support audit, incident response, data return or deletion, model-change notice, accessibility, and performance review. The organization remains accountable for a decision even when an external product supplies a score or recommendation (Ahiaeke Patrick *et al*., 2021; Mbonu *et al*., 2021; Sakyi *et al*., 2023; Mbonu *et al*., 2022; Memarian & Doleck, 2023).

Operational risk also deserves attention. Aggressive speed targets may reduce review quality. Volume incentives may encourage low-quality submissions. Candidate rediscovery may create duplicate ownership claims. Reused assessments may become stale. Global operations may introduce time-zone, language, payment, classification, tax, security, or mobility constraints. A risk register should assign each risk an owner, preventive control, detection measure, response, and escalation threshold. The paper therefore connects this claim directly to match quality, adverse impact, explainability, and post-hire performance.

Governance should support rather than obstruct better match quality, shorter time-to-supply, and stronger placement durability. Proportionate controls reduce rework and increase confidence. Clear definitions reduce disputes. Accessible processes retain qualified participants. Security protects organizational and personal interests. Documented review enables learning. The relevant choice is not speed or responsibility. The goal is a process whose speed results from clarity, reliable information, and prepared decisions (Ilodigwe & Adesemoye, 2021).

6.4 Illustrative application

Consider an organization operating in enterprise software staffing and digital talent platforms that experiences repeated delays and uneven outcomes. Leaders initially describe the problem as insufficient talent supply. Process mapping shows a more complex pattern: role requirements change after sourcing begins, reviewers apply different standards, participants receive generic messages, and onboarding access starts after acceptance. The organization selects one recurring role family for a twelve-month pilot.

During Demand specification, operational and technical leaders translate strategic demand into tasks, outputs, constraints, and proficiency levels. They remove two preferred credentials that lack a direct relationship with essential work and classify several skills as learnable during the first ninety days. This produces a stable demand brief and a baseline forecast. The organization records requirement changes instead of silently editing the role description.

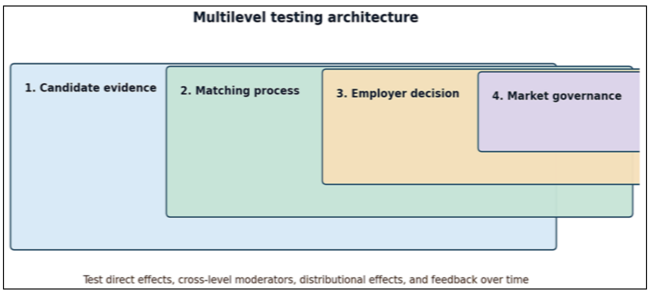
During Structured evidence capture, the workforce team develops an evidence map. Each essential capability has at least one acceptable form of evidence, such as a work sample, structured example, verified project, or calibrated assessment. Participants see the evidence requirements before investing time. Reviewers use the same rubric and record uncertainty. Accessibility checks identify a timed assessment whose format creates an unnecessary barrier, leading to a job-relevant alternative.

During Multidimensional matching, the organization

compares candidates across multiple dimensions and displays the basis of each recommendation. Reviewers receive a slate containing strong matches and selected near matches. One near match lacks experience with a named tool but demonstrates the underlying method and rapid learning in a comparable environment. Human review advances the person with a documented learning condition instead of allowing keyword absence to determine the result.
During Human validation, the manager completes an access and first-work checklist before the start date. The participant receives role expectations, key contacts, documentation, and an initial learning plan. Checkpoints occur after the first week, first meaningful output, first month, and third month. The organization distinguishes system access delays from individual performance and routes each issue to the correct owner.
During Post-placement learning, pilot leaders compare baseline and pilot results. They review cycle time by stage, qualified conversion, withdrawal, assessment burden, time to contribution, quality, satisfaction, subgroup progression, and correction cases. The group finds that total cycle time declined because clarification and access rework fell, even though structured review added time at one stage. This pattern demonstrates why end-to-end measures matter.
The scenario does not constitute empirical evidence. It shows how the framework organizes decisions and prevents premature conclusions. A real evaluation would report sample size, role context, definitions, missing data, comparison method, outcome period, and uncertainty. It would also document adverse or neutral findings. The value of the scenario lies in tracing mechanisms from design choices to observable measures (Ogundairo & Ayivi-Donkor, 2023; Ahiaeke Patrick *et al*., 2021).
A successful pilot would leave durable assets: an approved demand template, skills taxonomy, evidence map, reviewer rubric, communication sequence, readiness checklist, dashboard dictionary, governance charter, and change log. These assets convert individual expertise into an organizational capability. They also make later evaluation and replication more credible across teams pursuing better match quality, shorter time-to-supply, and stronger placement durability (Ilodigwe & Adesemoye, 2021).

6.5 Measurement and evaluation

The following framework translates the synthesis into a topic-specific structure for data-driven software talent matching.
Fig 4 presents the multilevel framework for empirical testing.



Source: Authors' conceptualization

Fig 4: Multilevel framework for empirical testing

Table 3 presents the multilevel evaluation matrix.

Table 3: Multilevel evaluation matrix

Level	Core question	Primary measure	Decision use
Candidate evidence	Are participants or workers gaining usable capability?	Competency, access, experience, and outcome gaps	Refine support and eligibility rules
Matching process	Does the delivery process work as designed?	Quality, timeliness, coordination, and exception rates	Redesign workflow and accountability
Employer decision	Does the organizational model create durable value?	Performance, retention, cost, risk, and distributional effects	Scale, pause, or revise the model
Market governance	Do external rules and conditions support responsible scale?	Compliance, inclusion, resilience, and stakeholder effects	Adjust governance and partnership terms

Measurement should answer decisions rather than decorate reports. The executive view should show strategic demand coverage, time to productive contribution, sustained quality, risk, and participant experience. The operational view should show waiting time, missing data, stage conversion, workload, rework, and exceptions. The governance view should show access, subgroup outcomes, complaints, overrides, incidents, and correction time (Ilodigwe & Adesemoye, 2021; Mbonu *et al*., 2018; Lawal & Oduleye, 2019; Akhigbe *et al*., 2023).
Demand measures include forecasted roles, approved demand, requirement volatility, cancelled demand, and the share of criteria mapped to observable tasks. Supply measures include reachable prospects, responsive participants, evidence completeness, qualified supply, availability, and concentration by source. These measures should remain separate because a large reachable pool may contain little relevant or available supply. For data-driven software talent matching, implementation fidelity determines whether this mechanism operates as proposed.
Flow measures include median and percentile time in each stage, conversion, withdrawal, rescheduling, assessment completion, reviewer delay, and rework. Medians hide extreme waits, while averages respond strongly to outliers. Reporting both a median and an upper percentile gives leaders a clearer view of typical experience and severe delay. Cohorts should be defined by entry date and tracked consistently. The paper therefore connects this claim directly to match quality, adverse impact, explainability, and post-hire performance.
Quality measures should reflect the work. Examples include milestone completion, error or rework rate, technical review, customer outcome, manager assessment, and participant self-assessment. Early performance measures require caution because manager readiness, access, assignment quality, and team context influence results. A single manager rating should not serve as unquestioned proof of match quality. Empirical tests should report variation in data quality, model governance, occupational change, and human oversight.

Experience measures include clarity, respect, accessibility, perceived relevance, support, and intent to remain engaged. Short surveys at major stages reduce recall error. Interviews or open-text analysis add context. Response rates and nonresponse patterns should accompany results. High satisfaction does not replace quality, and high quality does not excuse a confusing or inequitable process. This interpretation is specific to enterprise recruitment systems and should not be generalized without testing.

Fairness and risk measures include progression differences, incomplete assessments, false exclusion identified on review, override patterns, complaints, corrections, security incidents, and vendor changes. Analysis should use lawful, context-sensitive methods and avoid drawing conclusions from unstable small samples. Material differences should trigger investigation of criteria, data, access, communication, reviewer practice, and downstream conditions (Ahiaeke Patrick *et al*., 2021).

Review cadence should match the signal. Operational teams may examine flow weekly. Leaders may examine outcomes monthly or quarterly. Governance review should occur on a fixed schedule and after material incidents or system changes. Annual validation should test whether criteria, assessments, and models still represent current work. Owners should archive definitions and version changes so trends remain interpretable. In this analysis, the claim is assessed through match quality, adverse impact, explainability, and post-hire performance.

The final test is whether measurement changes decisions. For Data-driven software talent matching, leaders should predefine actions linked to thresholds. Examples include reopening a demand brief after repeated clarification, reviewing an assessment after disproportionate noncompletion, changing partner allocation after sustained quality problems, or pausing automation after unexplained drift. A dashboard without agreed action rules offers visibility but weak accountability.

6.6 Contextual adaptation and scale

The proposed model should be adapted to the operating realities of enterprise software staffing and digital talent platforms. Adaptation begins with the purpose of the workforce decision. A system designed for a short, low-risk assignment should not copy the controls of a regulated or safety-sensitive role. Likewise, a strategic position with scarce expertise requires more evidence, stronger stakeholder alignment, and a longer outcome horizon than a high-volume entry pathway. Proportionality protects both efficiency and decision quality. It also prevents organizations from presenting one workflow as a universal solution.

Scale changes the nature of the loss of information and fit across sourcing, assessment, matching, selection, and placement. At low volume, experienced staff often resolve ambiguity through direct conversation and tacit knowledge. As volume grows, undocumented judgment produces inconsistent outcomes, slower correction, and dependence on a few individuals. Standard definitions, decision records, calibrated rubrics, and shared data then become more important. Standardization should target recurring decisions while preserving an exception route for unusual profiles, emerging skills, accessibility needs, and changing project conditions (Ahiaeke Patrick *et al*., 2021; Mbonu *et al*., 2022; Ahmed & Odejobi, 2018).

Geographic expansion introduces further variation. Skill labels, credentials, compensation practices, communication norms, working hours, infrastructure, and legal requirements differ across markets. A portable framework should preserve the core questions while allowing local evidence. Organizations should validate whether assessments measure relevant capability across language and cultural settings. They should also separate genuine job constraints from inherited preferences. Local partners should contribute market knowledge, but shared governance should prevent inconsistent standards or unclear accountability. Empirical tests should report variation in data quality, model governance, occupational change, and human oversight.

Organizational maturity also shapes implementation. A small enterprise may rely on structured templates, a controlled spreadsheet, and a monthly review. A larger enterprise may connect applicant tracking, assessment, learning, identity, project, and performance systems. The larger technology stack creates integration and governance demands. More data does not guarantee better evidence. Teams should establish definitions, ownership, correction routes, and decision rules before automating data exchange or introducing predictive models (Mbonu *et al*., 2022; Michael & Ogunsola, 2023; Annan, 2022; Lawal & Oduleye, 2023).

Sustainable scale requires capability transfer. The model should not remain dependent on one designer, recruiter, analyst, manager, or vendor. Documentation, training, peer calibration, supervised practice, and periodic audits should build internal ownership. Partners should understand both performance expectations and ethical controls. Participants should receive consistent information and accessible support. These conditions convert a successful pilot into a repeatable organizational practice aligned with better match quality, shorter time-to-supply, and stronger placement durability.

Scaling decisions should use staged evidence. Leaders should first confirm process stability and data quality. They should then examine outcome improvement, participant experience, distributional effects, cost, and operational burden. Expansion should pause when definitions drift, error correction slows, outcome differences remain unexplained, or local teams lack ownership. A controlled scale-up protects the credibility of the framework and supplies clearer evidence for future research, policy, and investment decisions (Fadayomi *et al*., 2019; Akhigbe *et al*., 2023; Ilodigwe & Adesemoye, 2021).

6.7 Limitations

This paper presents a conceptual synthesis rather than original field data. The proposed relationships require testing across industries, countries, role levels, and organizational sizes. Published literature may underrepresent failed implementations and informal practices. Rapid changes in technology and regulation also limit the life of specific tools and examples. Within enterprise recruitment systems, its main boundary conditions are data quality, model governance, occupational change, and human oversight.

The framework does not assume global uniformity. Labor law, data protection, licensing, immigration, language, infrastructure, and cultural expectations shape feasible practice. Organizations should adapt implementation while preserving job relevance, transparency, accountability, and evaluation. Future studies should report context in enough detail to support responsible comparison (Mbonu *et al*., 2022; Mbonu *et al*., 2019).

6.8 Boundary conditions, rival explanations, and testable propositions

A stronger evaluation of data-driven software talent matching requires explicit boundary conditions. The proposed relationships should not be treated as universal across enterprise recruitment systems. Their direction and magnitude depend on data quality, model governance, occupational change, and human oversight. The framework therefore distinguishes necessary process conditions from contextual enablers. Clear demand information, credible evidence, documented decisions, supported transition, and outcome feedback form the process core. Context determines whether that core produces match quality, adverse impact, explainability, and post-hire performance. This distinction supports cumulative research because investigators can test the same mechanism in different settings without assuming identical effect sizes. It also protects practitioners from interpreting a conceptual framework as a fixed implementation recipe. A high-performing design in one organization may fail elsewhere when information quality, worker bargaining power, technology access, regulatory duties, or managerial follow-through differ. Future studies should report these conditions directly and explain how each condition shapes exposure to the intervention, the quality of implementation, and the interpretation of results.

Rival explanations also require direct attention. Improvements associated with data-driven software talent matching may reflect favorable labor-market timing, stronger leadership, higher budgets, employer reputation, changes in demand, or prior technology investments rather than the framework itself. Selection effects present another risk. Organizations willing to adopt structured practices may already possess better governance and stronger performance cultures. Worker outcomes may also improve because participants receive added attention during a pilot, not because the redesigned process changes underlying decisions. Research should address these alternatives through matched comparisons, phased implementation, interrupted time-series designs, or difference-in-differences analysis where data permit. Qualitative process tracing should accompany outcome analysis to establish whether the proposed mechanisms occurred in the expected sequence. Evidence of change without evidence of mechanism would support a weaker claim. Evidence of mechanism without improved outcomes would indicate implementation failure, a faulty causal assumption, or a contextual constraint requiring model revision.

Measurement validity is equally important. Studies should define match quality, adverse impact, explainability, and post-hire performance before implementation and separate leading indicators from final outcomes. Activity counts, including messages sent, profiles screened, meetings held, or training sessions completed, do not establish value. Stronger measures connect process exposure to decision quality, participant experience, operational performance, and durability over time. Each construct should have an operational definition, a data source, a measurement interval, and a responsible owner. Multi-item measures should report internal consistency where appropriate. Administrative measures should undergo completeness and error checks. Ratings should use anchored criteria and inter-rater reliability tests when human judgment affects scoring. Fairness analysis should compare relevant groups while protecting privacy and avoiding unsupported causal interpretations. Researchers should report missing data, attrition, changes in definitions, and any outcome selected after analysis began. These practices reduce outcome switching and make replication more credible.

The framework generates falsifiable propositions. First, organizations applying the complete process core should achieve stronger match quality, adverse impact, explainability, and post-hire performance than organizations applying isolated tools, after accounting for baseline differences. Second, the relationship should weaken when data quality, model governance, occupational change, and human oversight create severe implementation constraints. Third, decision transparency and structured human review should mediate the relationship between information quality and perceived fairness. Fourth, transition support should mediate the relationship between selection quality and sustained performance. Fifth, feedback quality should moderate long-term effects because organizations that examine errors and unequal outcomes should adapt faster than organizations that track activity alone. A proposition should be rejected or revised when the expected mechanism fails to appear, when effects move consistently in the opposite direction, or when benefits depend on unacceptable harms. Stating these failure conditions turns the framework into a research program rather than an unfalsifiable list of preferred practices.

Research design should reflect the level at which each mechanism operates. Individual-level data capture access, experience, learning, and performance. Team-level data capture coordination, workload, and supervisory practice. Organizational data capture governance, investment, and strategic outcomes. Network or regional data capture spillovers, mobility, institutional capacity, and distributional effects. Analysts should avoid drawing organizational conclusions from individual perceptions alone or attributing individual outcomes to aggregate trends. Multilevel models, clustered standard errors, or carefully bounded case comparisons can address dependence within teams and organizations. Longitudinal designs are preferred because early conversion gains may disappear if placements fail, work quality declines, or participants exit. Reporting should include baseline equivalence, exposure duration, implementation fidelity, subgroup results, sensitivity tests, and negative findings. These elements help reviewers distinguish a credible test from a descriptive success story. For data-driven software talent matching, implementation fidelity determines whether this mechanism operates as proposed.

For practice, the central implication is disciplined experimentation. Leaders should specify the problem, select a bounded unit, record baseline measures, document the intervention, assign decision rights, and establish stopping rules before launch. The pilot should include process, outcome, fairness, and risk measures. Review meetings should examine where the causal chain broke, whose outcomes improved, whose outcomes worsened, and which contextual constraint explains the difference. Scaling should follow evidence of stable performance across more than one cycle. When results are mixed, leaders should revise the mechanism or narrow the claim instead of treating adoption as success. This approach aligns implementation with the evidentiary standard expected of a mature conceptual contribution. It also creates a clear bridge between the present synthesis and future empirical studies capable of confirming, qualifying, or rejecting its propositions. The paper therefore connects this claim directly to match quality, adverse impact, explainability, and post-hire performance.

7. Conclusion and future research

Data-driven software talent matching requires more than increased sourcing activity. The core challenge is to connect demand, evidence, interaction, decisions, transition, and learning. The five-stage framework offers a structured route from fragmented practice toward better match quality, shorter time-to-supply, and stronger placement durability.

The framework should be treated as a testable operating model. Organizations should start with a bounded pilot, establish a baseline, assign decision owners, measure both benefits and harms, and revise the design from outcomes. Research should test the propositions with transparent methods and disaggregated measures. A workforce system earns value when it helps people and organizations make better decisions, correct errors, and convert capability into sustained contribution. Empirical tests should report variation in data quality, model governance, occupational change, and human oversight.

8. CRediT authorship contribution statement

Rasheed Akhigbe: Conceptualization, methodology, investigation, formal analysis, writing - original draft, and writing - review and editing. Miracle Wikiri: Conceptualization, methodology, validation, supervision, and writing - review and editing. Chioma Ann Udeh: Validation, literature review, and writing - review and editing. This interpretation is specific to enterprise recruitment systems and should not be generalized without testing.

9. Declaration of competing interest

The authors declare no competing interests.

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11. Data availability

No new dataset was generated or analyzed for this conceptual review.

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